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RESEARCH PAPER

A New Damage Detection Approach Under Variable Environmental or Operational Conditions

Jalalifar, F.[1], Esfahani, M.R.[2*] and Shahabian Moghadam, F.[2]

[1] Ph.D. Candidate, Civil Engineering Department, Faculty of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran.
[2] Professor, Civil Engineering Department, Faculty of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran.

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ABSTRACT: The basic idea of vibration-based damage identification approaches is that damage causes change in vibration response of structure. So monitoring the vibration response characteristics can be helpful in damage detection. The main limitation in such methods is that these characteristics are also affected by the Environmental and Operational Variability (EOV) that can be incorrectly known as structural damage or sometimes cover actual damages. This paper aims to propose an innovative approach to detect and locate damage considering the EOV conditions. In this regard, an Independent Component Analysis (ICA) based Blind Source Separation (BSS) approach is employed to remove the EOV influences from the time history response of the structure. The beneficial of using the ICA-based BSS method is that there is no need to measure the environmental/operational conditions. Moreover, it is able to remove EOV influences using a limited group of response data monitored during different environmental and operational conditions. Time series analysis is then performed to extract damage-sensitive features. Finally, a statistical tool is employed to damage identification and localization by using EOV independent features. Two recognized benchmark structures are employed for verifying the accuracy of the proposed approach. Results indicate that the proposed method is a time-saving tool and efficiently successful in damage assessment of structures under EOV.

Keywords: Bhattacharyya Measure, Blind Source Separation, Damage Detection, Environmental and Operational Variability, Time Series Analysis.

1. Introduction

Monitoring structural damage plays a critical role in the maintenance of civil structures and has several economic benefits. Several methods such as thermography, optical methods, ultrasonic testing, acoustic emission, and vibration-based methods have been developed to diagnose structural damage (Avci et al., 2021). Among these methods, vibration-based methods are of great importance as they can detect damage remotely by sensors.

Utilizing the statistical pattern recognition techniques in vibration-based

[*] Corresponding author E-mail: esfahani@um.ac.ir

damage detection methods leads to an effective data-driven methodology which have attracted much attention in Structural Health Monitoring (SHM) applications. These methods consist of using vibration time domain responses, feature extraction by time series analysis, and damage identification through statistical decision making (Entezami, 2021). Roy et al. (2015) employed different time series models to obtain damage-sensitive features using output-only measurements. They used a statistical distance test for damage localization. Datteo et al. (2017) employed the principal component analysis of AutoRegressive (AR) parameters to condition assessment of a stand of the Giuseppe Meazza stadium in Milan during a long-term vibration monitoring. Razavi et al. (2021) proposed a data-driven method for vibration-based damage detection. In the proposed method, feature extraction is based on time series analysis and then damage is localized by two statistical distance measure called Jeffery's and Smith's distances. More applications of statistical pattern recognition techniques to SHM can be found in (Zhang and Song, 2018; Entezami et al., 2019; Daneshvar et al., 2021; Kordi and Mahmoudi, 2022).

The damage detection in vibration-based methods is based on the assumption that damage affects the structural dynamic properties that change the vibration response characteristic (Limongelli et al., 2021). However, the responses measured in these methods are sensitive not only to damage but also to EOV (Vamvoudakis-Stefanou et al., 2018). In SHM literature, the sensitivity of structural responses has been reported to environmental and operational items including temperature, wind, humidity, traffic and water level within the dam (Bayraktar et al., 2014; Comanducci et al., 2016; Nguyen et al., 2017; Hu W-H, 2018; Cunha et al., 2019; Kullaa, 2020). Consequently, before extracting damage sensitive features, the effects of the EOV must be considered. Cross (2012) introduced this issue as the data normalization problem. A literature review presents different approaches proposed for dealing with the EOV effects. Some of these approaches try to model the effect of EOV on monitoring parameters or damage sensitive features (Spiridonakos et al., 2016; Cai et al., 2021; Shan et al., 2018). Therefore, the prediction error is a robust indicator of a structural condition that is insensitive to EOV. The simplest approach to model the effects of EOV on damage-sensitive features contains the linear regression model (Cross et al., 2013; Dervilis et al., 2015). Several approaches containing neural networks and support vector machines can be found in the literature dealing with the modeling the effect of EOV (Zhang et al., 2018). The primary restriction of such approaches is due to a set of changing conditions that must be identified and accurately measured. Nevertheless, these approaches may not be a good choice when several environmental or operational items are considered.

Several alternative strategies have been investigated when it is not feasible to measure the environmental/operational conditions. The most popular of these strategies rely on using a group of response data monitored during a long enough time period to span all the possible normal conditions. Handling a huge amount of data is the main limitation of this strategy. Furthermore, having a large database from normal conditions may reduce features sensitivity to damage (Cross, 2012).

Considering the above-mentioned practical difficulties, this paper aims to employ a Blind Source Separation technique (BSS) to suggest a new approach for data normalization. BSS technique has been accepted as an effective solution for analysis of traffic-induced vibrations (Chen et al., 2015), modal identification (Yu, 2019; Sadhu et al., 2017), and condition monitoring (Guo and Kareem, 2016). Sadhu and Hazra (2013) proposed a new damage detection method including BSS technique and time-series analysis. In this algorithm, the modal response is estimated from the vibration measurements utilizing the BSS technique and then one-step-ahead prediction of the modal response is performed by means of time-series analysis. Rainieri et al. (2019) employed the Second-Order Blind Identification (SOBI) to model the variability of natural frequency estimates under EOV. In this paper, an ICA-based BSS method is employed to remove the EOV influences from the time history response of the structure.

In the damage assessment approach proposed in this paper, a BSS approach is employed to remove the effects of the EOV on the time history response of the structure in the presence of unmeasured EOV. Then, time series analysis is applied to extract damage sensitive feature from the EOV independent response of the structure. Finally, a statistical tool called Bhattacharyya measure is introduced for damage identification and localization.

This paper includes different sections as follows: Section 2 indicates the novelty and importance of the present work. Section 3 describes the mathematical foundations of techniques used in the proposed approach. Section 4 presents the steps of the proposed damage assessment approach. In Section 5, the proposed method is applied to data acquired from two benchmark structures. A comparative study also is conducted to demonstrate the capability of the proposed approach. Finally, Section 6 provides the conclusion.

2. Research Significance

This paper proposes a statistical pattern recognition approach to detect and locate damage in structures considering the EOV conditions. The effect of EOV on the system's vibration signal is a challenging issue in application of vibration-based damage detection methods. This paper employs an ICA-based BSS method to suggest a new approach to remove the EOV influences from the time history response of the structure. This approach is able to remove EOV influences using a limited group of response data monitored during different environmental and operational conditions. It is worth to mention that in the proposed method, the measurement of environmental or operational items is unnecessary.

In the proposed damage detection method, a time series analysis is applied to extract damage sensitive feature from the EOV independent response of the structure. In this method, in contrary with model based methods, there is no need to analytical or physical modeling of the structure and only use time-domain data.

Finally, a novel statistical method named as Bhattacharyya measure is introduced to measure the degree of similarity between damage sensitive features obtained in different conditions of structure for damage detection.

In calculating the Bhattacharyya measure, feature vector is divided into several subdivisions and the numerical information of them, like the number of total subdivisions and the number of samples within each subdivision, are used. In the other word, the features is not directly involved in the Bhattacharyya measure calculation. Therefore, it can be able to be regarded as a solution for the issue of large data or high-dimensional features.

3. Theoretical Background

The algorithm developed in this paper employs the BSS method to eliminate the effects of EOV from the structural responses. After that, time series analysis is employed to extract damage sensitive features. Finally, Bhattacharyya measure is used for damage detection and localization. Theoretical background of BSS method, time series analysis and Bhattacharyya measure are included herein.

3.1. Blind Source Separation (BSS)

The objective of BSS technique is to retrieve the unobserved source signals from the mixture observations carried out by an array of sensors. In this paper, the sources refer to the responses of the structure to unmeasured environmental and operational conditions that cause the responses of the structure in a certain state be uncertain. Figure 1 shows a BSS problem.

$$\begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix} = s \rightarrow A \xrightarrow{x} U \rightarrow y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \hat{s}$$

Fig. 1. Mixing and separating; Unknown sources: *s*, Observations: *x*, Estimated sources: $\hat{s}$, Mixing matrix: *A*, Demixing matrix: *U* (Jain and Rai, 2012)

The BSS model considers the N source signals and the M observations as $s(t) = (s_1(t), \dots, s_N(t))^T$ and $x(t) = (x_1(t), \dots, x_M(t))^T$ respectively. Now, the BSS model can be expressed as,

$$\begin{aligned} x(t) &= As(t) \\ \hat{S}(t) &= Ux(t) \end{aligned} \tag{1}$$

BSS methods' purpose is to find the demixing matrix *U* and the sources $\hat{s}(t)$ based on observations of the $x(t)$ alone. A literature review reveals several BSS approaches. In this paper, Independent Component Analysis (ICA) is applied to remove the EOV effect.

3.1.1. Independent Component Analysis (ICA)

Independent Component Analysis is greatly utilized in various fields such as blind separation of mixed voices or images, biomedical signal processing, data communication and several others. Recently ICA is extended for damage detection and condition monitoring (Jiang et al., 2019; Wang et al., 2020). There are different ICA algorithms in the literature (for example Joint Approximate Diagonalization of Eigenmatrices (JADE) and Natural Gradient algorithms). The proposed approach in this paper utilizes the JADE algorithm.

Cardoso and Souloumica (1993) proposed the JADE as an algorithm for ICA by a joint approximate diagonalization of eigenmatrices. The approach combines second and fourth order statistics to perform BSS of the mixtures. Due to space limitation, fundamental steps of JADE algorithm are indicated. The reader can refer to Cardoso (1999) for further detail.

Referring to Eq. (1), *X*: is a set of observations and *A*: is an unknown mixing matrix. The goal is then to estimate a demixing matrix, $U = A^{-1}$. Supposing that the sources are independent, four fundamental steps are needed to obtain the demixing matrix.

1. Estimating a whitening matrix *W* and calculating the whitened matrix Z which $Z = WX$.
2. Estimating the cumulant matrices $\{Q_i^Z\}$.
3. Estimating the matrix *V* using joint approximate diagonalization (JAD) algorithm as

$$V = argmin \sum_i 0ff\left(V^T Q_i^2 V\right) \tag{2}$$

4. Estimating the demixing matrix $[U]$ and the sources $\{s(t)\}$which

$$\begin{aligned} [U] &= [V]^T[W] \\ \{s(t)\} &= [U]\{x(t)\} \end{aligned} \tag{3}$$

3.2. Time Series Analysis

Time series analysis is a statistical way trying to fit a mathematical model over time-series observations in order to determine specific statistics. There are several model for analyzing the time series data. Entezami and Shariatmadar (2019) suggested that when the measured response of the structure is resulting from the ambient excitations, it should be better to model the structural response by applying time series models that contain a polynomial equation into the error term. In this regard, the ARMA and ARARX models can be efficiently employed for modeling the time history measurements under the ambient excitations. If time series signal is an AR process in nature, the ARARX model is a better choice (Ljung, 1999). To determine the nature of time series data, the Box-Jenkins methodology can be used efficiently (Box et al., 2015). In the benchmark structures considered in this paper, the ARARX model is used.

Suppose that $x(t)$ is a stationary and linear time series, then AR(p) model is indicated as:

$$x(t) = \sum_{j=1}^{p} \varphi_{xj} x(t-j) + e_x(t) \tag{4}$$

in which $e_x(t)$: is the random error, φ_{xj}: denotes the AR coefficients, and p: is the order of the model. Structurally, the ARX model and the AR model are identical. The difference is that the ARX model contain a regression term for an external input $e(t)$. In the employment of an ARARX model, the residuals of the AR model are applied as the external input in the ARX model.

$$x(t) = \sum_{i=1}^{a} \alpha_i x(t-i) + \sum_{j=1}^{b} \beta_j e_x(t-j) + \varepsilon_x(t) \tag{5}$$

where α_i and β_j: are the ARX coefficients, $\varepsilon_x(t)$: is the ARX random error, and a and b: are the order of the model.

In application, damage sensitive feature might be selected from particular characteristics of the residuals achieved by fitting a model from reference condition $x(t)$ to $y(t)$ measured from an unknown condition.

$$y(t) = \sum_{j=1}^{p} \phi_{yj} y(t-j) + e_y(t) \tag{6}$$

$$\varepsilon_y(t) = y(t) - \sum_{i=1}^{a} \alpha_i y(t-i) + \sum_{j=1}^{b} \beta_j e_y(t-j) \tag{7}$$

3.3. Bhattacharyya Measure

Bhattacharyya measure reflects the degree of similarity between any two statistical samples. Suppose that $p(i)$ and $p^{'}(i)$ are two samples, including N partitions with respective probabilities $p(i = 1), \ldots, p(i = N)$ and $p^{'}(i = 1), \ldots, p^{'}(i = N)$. The Bhattacharyya measure is defined as:

$$\rho(p, p') = \sum_{i=1}^{N} \sqrt{p(i) p'(i)} \tag{8}$$

From the geometric view, the Bhattacharyya measure is the cosine of the angle between the vectors $\left(\sqrt{p(i)} \ldots\ldots \sqrt{p(N)}\right)^T$ and $\left(\sqrt{p'(i)} \ldots\ldots \sqrt{p'(N)}\right)^T$. To obtain Bhattacharyya measure between two damage-sensitive feature vectors, each vector should be divided into N partitions, after determining the probability of each partition, the Bhattacharyya measure is calculated according to Eq. (8).

4. Proposed Method

Suppose that there is a significant amount of variability in the measured data from an undamaged structure due to EOV. The proposed method takes advantage of the JADE algorithm to filter the confounding effects of EOV. The JADE algorithm makes the measured data independent of one another and obtains the sources. Therefore, if in a time period, the data from the undamaged structure subject to EOV conditions are recorded, one can acquire the independent sources. Discarding the sources that account for significant amounts of variability in the data, the confounding effects of EOV are filtered.

A critical aspect of the application of the JADE algorithm is the determination of the number of sources (m). Like the PCA, a smaller number of measured data are responsible for the total variability in data. This happens when some of the eigenvalues of the covariance matrix become equal to zero. In practical applications, owing to the noise and numerical precision issues, the eigenvalues do not become exactly equal to zero. Instead, the number of sources, which account for most of the variabilities, can be determined when a clear drop in the eigenvalues is observed. Here, the following indicator is used to determine *m*:

$$I = \frac{\sum_{i=1}^{m} \sigma_i^2}{\sum_{i=1}^{n} \sigma_i^2} \tag{9}$$

The steps of the proposed damage assessment framework are as follows. First, the JADE algorithm is applied into a set of acceleration time history measurements from an undamaged state (or reference state) measured in different environmental and operational conditions, and the sources are obtained. Concerning *m* in Eq. (9), the number of sources is determined as *m*+1. The last source is selected as an independent source from EOV effects. Then, the independent source is modeled using an appropriate time series model as presented in Subsection 2.2 and the residuals are calculated. With the arrival of acceleration time history measurements from the current state, the independent source is also obtained using the JADE algorithm. After that, the time series model applied in the reference state is used to model the independent source from the current state and the residuals are calculated. Finally, the Bhattacharyya measure is determined between the residuals from reference and current states and considered as a damage index. The flowchart of the suggested approach is showed in Figure 2.

5. Application

To support the proposed method and to demonstrate the usefulness of the JADE algorithm for compensating the influences of EOV, two well-known benchmark models in the SHM community are investigated. The first is a simulated beam structure under changing environmental and operational conditions. The second is a laboratory wooden bridge with actual environmental variability.

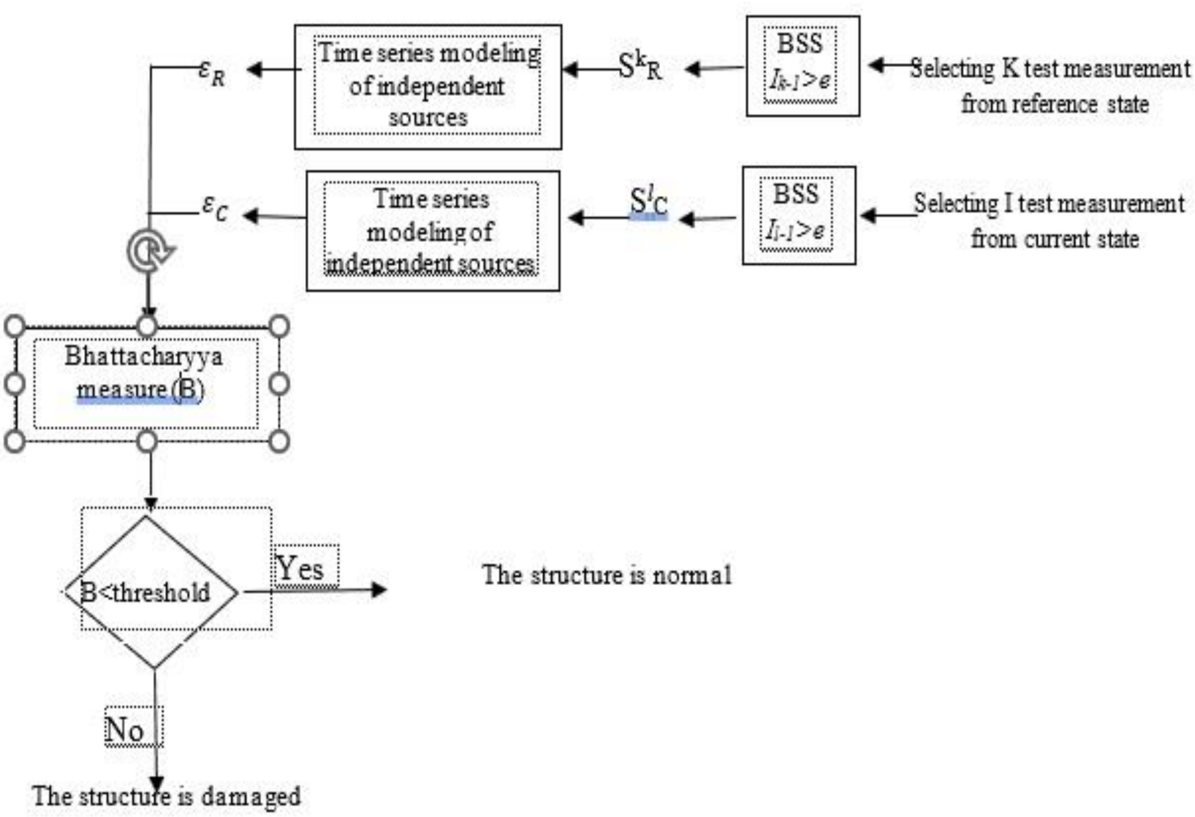


Fig. 2. Flowchart of the proposed method

5.1. Beam Structure with Environmental and Operational Changes

The considered structure is a simply-supported steel beam simulated by Kullaa (2014) and is showed in Figure 3. The length and cross-section of the beam is 1.4 m and 50 × 5 mm, respectively. According to Figure 3, the structure contains a spring in 612.5 mm from the support with spring constant k as:

$$k = k_0 + aT^3 \tag{10}$$

where k_0 = 100 kN/m, a = –0.8 (with compatible units), and T: is temperature with a uniform random distribution between -20 and +40 °C.

The beam consists of three equal length parts. The Young's modulus of each part E_i is:

$$E_i = E_0 + \sigma_i z_i, \qquad i = 1,2,3 \tag{11}$$

where E_0 = 207 GPa and z_i: is the environmental variable with standardized Gaussian distribution and the standard deviations (σ_i) of different parts are 5, 3 and 7 GPa, respectively.

Damage is simulated by the beam depth reduction on a length of 19.4 mm at the spring support. Sensor 21 is at the center of the damaged zone. The beam depth reduction differs in five levels: 0.5, 1, 1.5, 2, and 2.5 mm.

The proposed method is applied to the acceleration measurements of the beam structure. First, 10 measurements from the undamaged beam as a reference data set (R), 10 measurements from the undamaged beam as a health data set (H), and 10 measurements from each five damaged state as damaged data sets (D1, D2, D3, D4, and D5) are selected. Then, the sources are obtained from each dataset using the JADE algorithm. The 10th source is chosen as an independent source in each state. Based on Section 2.2, the ARARX model is selected for time series modeling. Finally, the Bhattacharyya measure is calculated between residuals of the reference state and those of each state. The mentioned steps are repeated for each Degree Of Freedom (DOF).

To determine the threshold value, after estimating the Bhattacharyya measure of health state in each DOF, the mean and standard deviation of them are obtained. Supposing normal distribution for Bhattacharyya measure, the threshold is set at the point under which 1% values occur. Here, the threshold value is 0.8059. The damage index beyond the threshold value means the structure is healthy and under that indicates a damaged state.

Figure 4 illustrates the Bhattacharyya measure in different structural states. As the number of DOF is too large, only odd DOFs are shown. As can be seen from Figure 4, the damage index in healthy states is beyond the threshold value in all DOFs. About the damaged states in DOF 11 to 29, the damage indices are under the threshold value except for a few errors. In few initial and final DOF, the damaged states D1 and D2 are not recognized due to be far from the damage location. In DOF 21, the Bhattacharyya measure in damaged states is lower than that of other DOFs showing damage location. In point of damage severity, the damage index decreased while damage severity increased as denoted in Figure 4. However, there are a few errors that it will be discussed later.

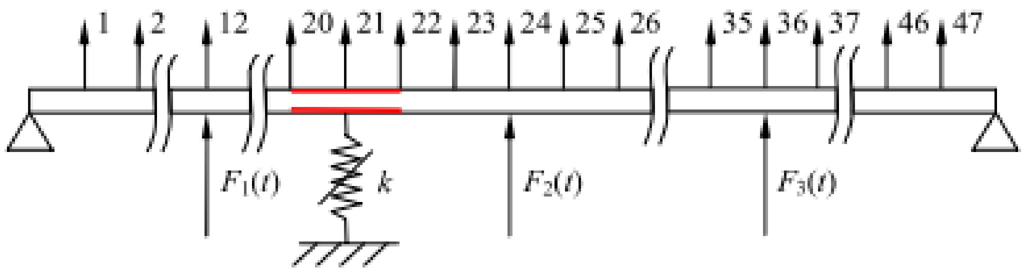


Fig. 3. Simply-supported beam (Kullaa, 2014)

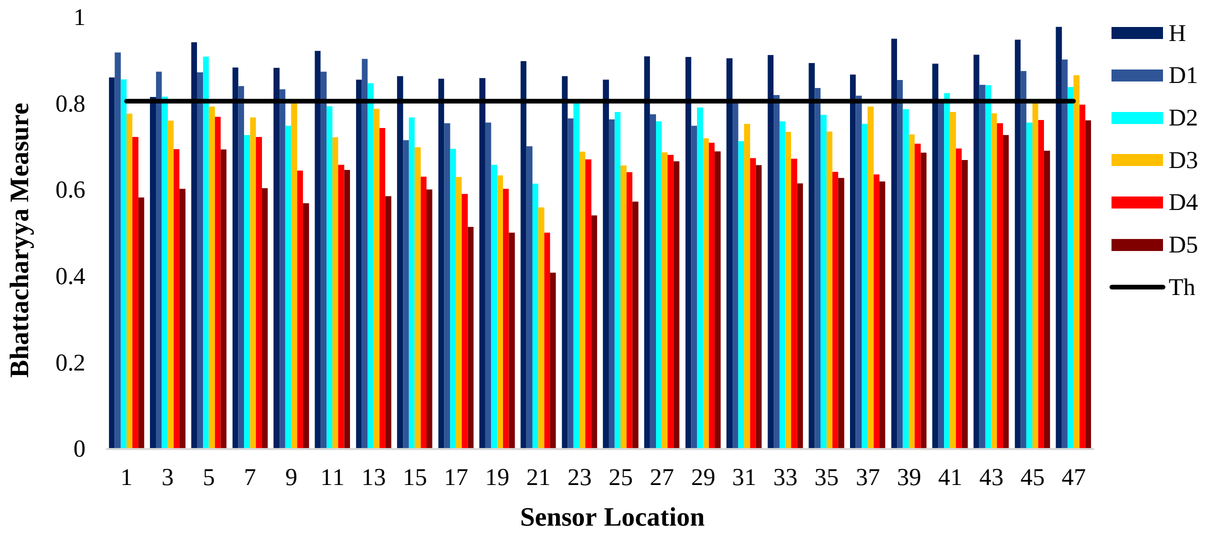


Fig. 4. The Bhattacharyya measure of odd DOFs of beam structure in different structural states

Investigating the cause of errors in Figure 4, the values of the indicator I in Eq. (9) are considered for m = 9. These values in each DOF and different damage states are shown in Table 1. As it is clear in all error cases, the indicator I is less than 0.97. This reveals that in such cases, the EOV effects have not been effectively eliminated and the obtained sources are not independent of EOV. So, in these cases, more data measurements are needed in a relevant data set. In Figure 5, the cases that I < 0.97 are deleted. In each DOF, as the damage severity increases, the damage index decreases.

It is notable to mention that the proposed method is able to identify the damage location even in the small damage scenarios like the states D1 and D2.

Table 1. The value of indicator I in Eq. (9) when m = 9

DOF	Structural state						
	R	**H**	**D1**	**D2**	**D3**	**D4**	**D5**
1	0.989	0.995	0.964	0.979	0.972	0.990	0.988
3	0.989	0.995	0.963	0.978	0.972	0.990	0.989
5	0.991	0.995	0.960	0.975	0.973	0.990	0.990
7	0.993	0.996	0.975	0.955	0.978	0.992	0.994
9	0.992	0.994	0.976	0.961	0.979	0.991	0.993
11	0.990	0.997	0.974	0.992	0.977	0.996	0.992
13	0.991	0.996	0.966	0.983	0.975	0.993	0.992
15	0.994	0.996	0.957	0.973	0.977	0.991	0.994
17	0.992	0.993	0.975	0.974	0.975	0.990	0.992
19	0.991	0.994	0.974	0.974	0.970	0.988	0.987
21	0.992	0.993	0.977	0.971	0.972	0.987	0.991
23	0.994	0.992	0.980	0.965	0.970	0.980	0.991
25	0.995	0.992	0.984	0.968	0.971	0.979	0.991
27	0.992	0.992	0.978	0.972	0.972	0.984	0.987
29	0.989	0.993	0.975	0.961	0.970	0.987	0.984
31	0.991	0.992	0.982	0.957	0.971	0.985	0.985
33	0.991	0.992	0.981	0.980	0.972	0.986	0.986
35	0.990	0.993	0.973	0.973	0.971	0.989	0.985
37	0.988	0.993	0.973	0.972	0.969	0.990	0.983
39	0.991	0.990	0.986	0.981	0.971	0.974	0.984
41	0.993	0.991	0.985	0.962	0.971	0.981	0.990
43	0.992	0.993	0.975	0.970	0.973	0.985	0.988
45	0.991	0.994	0.970	0.964	0.970	0.987	0.992
47	0.991	0.994	0.975	0.966	0.970	0.988	0.985

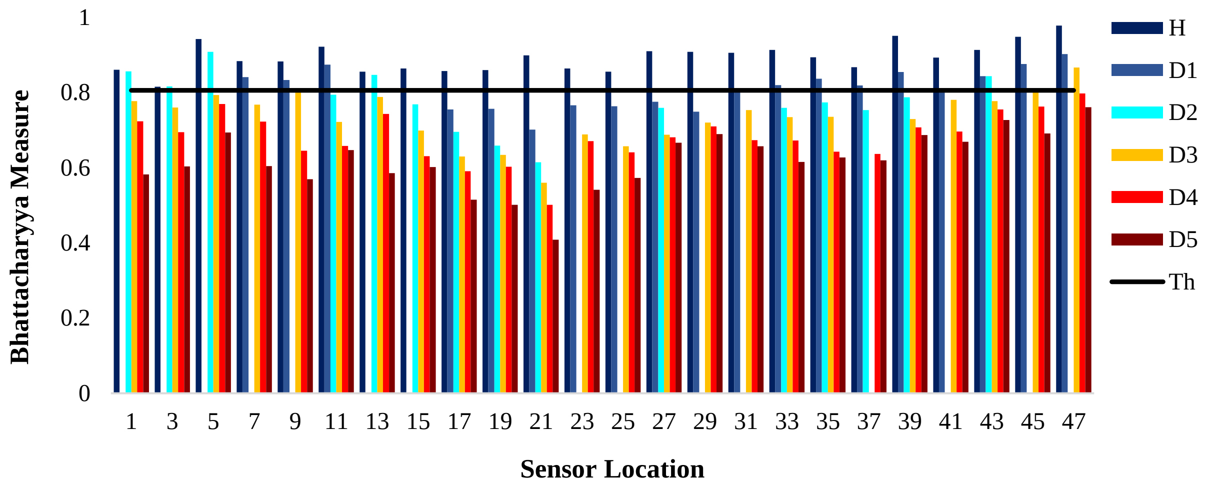


Fig. 5. The modified Bhattacharyya measure of beam structure in different structural states

To demonstrate the capabilities of the suggested approach, it is compared with the damage detection method suggested by Sohn and Farrer (2001). In Sohn and Farrer's method, an AR(p) model is applied to all measurements from a reference database. After estimating AR coefficients of the measurement *y(t)* from unidentified state, the reference dataset *x(t)* whose AR coefficients approximate those of *y(t)*, is chosen. Next, the chosen *x(t)* is modeled by an ARX (α,β). So, $\varepsilon_x(t)$ and $\varepsilon_y(t)$, the ARX residual of *x(t)* and *y(t)*, are estimated. Finally, the ratio $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ is determined being the damage-sensitive feature, while $\sigma(\,)$ is the standard deviation. The increase in this ratio is monitored to detect damage and is anticipated to reach its peak value near the damage location. Furthermore, a hypothesis test is applied to examine if the new measurement *y(t)* and the baseline measurement *x(t)* are considerably different. A more detailed discussion of this method can be found in Sohn and Farrer (2001). To employ the indicated method, 40 measurements from the health state of the beam structure measured under EOV are chosen as the reference database. Next, from each structural state, 10 datasets are picked as test datasets. Table 2 presents the $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ ratio for odd DOFs and all structural states. The values presented are the mean values of 10 sample standard deviation ratios for each structural state. Regarding Table 2 in damaged states, the highest increase in $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ ratio is at DOF 21 (damage location). Moreover, as damage severity increases, the standard deviation ratio also increases as well.

The results of hypothesis tests are outlined in Table 3. The values in Table 3 show among all hypothesis tests how many null hypothesis are rejected. For example, 2/10 means that from 10 hypothesis test applied on data sets, the rejection number is 2. Normally, in the health condition the rejection numbers are low, though in damaged condition many rejections are reported. Besides, maximum value of the rejections shows the damage location.

Results show that Sohn and Farrer's method has been able to effectively determine structural state and damage location. Meanwhile, the reference database in this method contains 40 test measurements and in the proposed method there are only 10 test measurements. Besides, the analysis time by MATLAB in the Sohn and Farrer's method is 2328 s while it is 196 s in the proposed method. Once again, the beam structure is analyzed using Sohn and Farrer's method. This time the number of test measurements in the reference database is 10. In this case, the analysis time is 1663 s. Table 4 demonstrates the hypothesis test results in a healthy structure. Table 4, reveals that having a reference database with 10 test measurements, the Sohn and Farrer's method is not successful in damage detection. As a conclusion from these analyses, it can be stated that the proposed method compared with Sohn and Farrer's method can present good results using fewer measurements from the reference state of the structure in a shorter analysis time.

5.2. Wooden Bridge with Actual Environmental Variability

The second considered structure is a wooden bridge under real environmental variability presented by Kulla (2011). Figure 6 shows the laboratory setup. The acceleration is measured by 15 sensors at three different longitudinal positions with a 256 Hz sampling frequency. The measurement is accomplished under temperature and humidity variations during several days. Damage is simulated by attaching point masses on the top flange close to sensor 4 (Figure 6). The weight of the masses varies in five sizes: 23.5, 47.0, 70.5, 123.2, and 193.7 g. With regard to the total weight of the structure (36 kg), the attaching point masses are very small.

Table 2. The mean value of $\sigma\left(\varepsilon_y\right) / \sigma\left(\varepsilon_x\right)$ in different structural states

Structural state	DOF 1	3	5	7	9	11	13	15	17	19	21	23
H	1.016	1.018	1.010	1.010	1.073	1.002	1.029	1.015	1.010	1.022	1.035	1.016
D1	1.015	1.022	1.016	1.019	1.028	1.016	1.019	1.427	1.353	1.895	2.088	1.782
D2	1.018	1.024	1.018	1.019	1.024	1.290	1.480	1.453	1.460	2.076	2.565	1.981
D3	1.020	1.018	1.024	1.306	1.264	1.427	1.667	1.800	2.228	2.588	3.259	2.733
D4	1.368	1.212	1.456	1.396	1.602	1.647	1.686	1.881	2.584	2.925	3.513	2.840
D5	1.397	1.351	1.414	1.431	1.653	1.621	1.792	2.420	3.138	3.735	4.349	3.414

Structural state	DOF 25	27	29	31	33	35	37	39	41	43	45	47
H	1.027	1.018	1.012	1.004	1.017	1.015	1.025	1.001	1.016	1.016	1.012	1.015
D1	1.704	1.508	1.550	1.334	1.029	1.020	1.025	1.017	1.019	1.015	1.016	1.030
D2	1.792	1.610	1.595	1.450	1.246	1.026	1.024	1.015	1.021	1.016	1.020	1.025
D3	2.045	1.695	1.653	1.501	1.321	1.398	1.353	1.214	1.022	1.020	1.025	1.015
D4	2.331	1.830	1.717	1.576	1.555	1.598	1.563	1.257	1.199	1.266	1.158	1.291
D5	2.930	2.256	2.173	2.055	1.930	1.958	1.893	1.475	1.498	1.469	1.546	1.400

Table 3. The result of hypothesis tests in different structural states

Structural state	DOF 1	3	5	7	9	11	13	15	17	19	21	23
H	0/10	1/10	0/10	0/10	1/10	0/10	0/10	0/10	0/10	0/10	0/10	0/10
D1	0/10	1/10	0/10	1/10	0/10	0/10	1/10	6/10	6/10	10/10	10/10	10/10
D2	1/10	2/10	1/10	1/10	1/10	4/10	7/10	6/10	7/10	10/10	10/10	10/10
D3	0/10	0/10	2/10	5/10	5/10	6/10	9/10	9/10	10/10	10/10	10/10	10/10
D4	6/10	3/10	7/10	6/10	8/10	8/10	9/10	10/10	10/10	10/10	10/10	10/10
D5	6/10	6/10	6/10	6/10	8/10	8/10	10/10	10/10	10/10	10/10	10/10	10/10

Structural state	DOF 25	27	29	31	33	35	37	39	41	43	45	47
H	1/10	0/10	0/10	0/10	0/10	0/10	1/10	0/10	0/10	0/10	0/10	0/10
D1	9/10	7/10	7/10	6/10	1/10	0/10	1/10	0/10	0/10	0/10	0/10	1/10
D2	10/10	8/10	8/10	7/10	5/10	1/10	1/10	0/10	1/10	0/10	1/10	1/10
D3	10/10	9/10	9/10	7/10	5/10	6/10	5/10	4/10	1/10	1/10	2/10	1/10
D4	10/10	10/10	10/10	7/10	7/10	7/10	7/10	5/10	4/10	5/10	3/10	4/10
D5	10/10	10/10	10/10	10/10	10/10	10/10	10/10	7/10	7/10	7/10	7/10	6/10

Table 4. The result of hypothesis tests in heath state with 10 measurements in the reference database

DOF	1	3	5	7	9	11	13	15	17	19	21	23
H	8/10	7/10	6/10	8/10	7/10	8/10	9/10	8/10	6/10	8/10	8/10	7/10
DOF	25	27	29	31	33	35	37	39	41	43	45	47
H	6/10	7/10	8/10	8/10	8/10	7/10	8/10	9/10	7/10	8/10	8/10	9/10

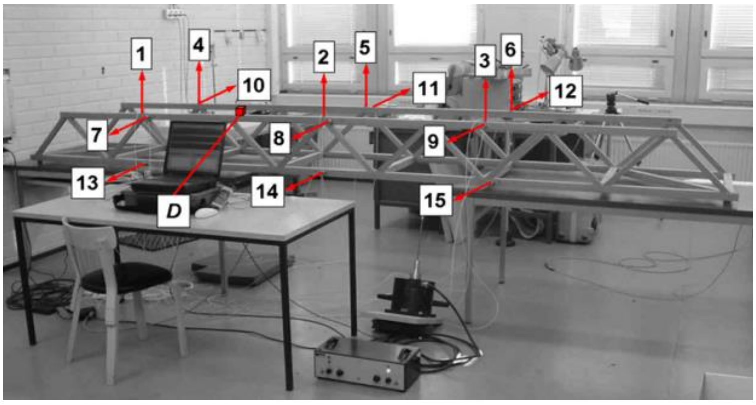


Fig. 6. Wooden bridge with the location of sensors and damage (*D*) (Kulla, 2011)

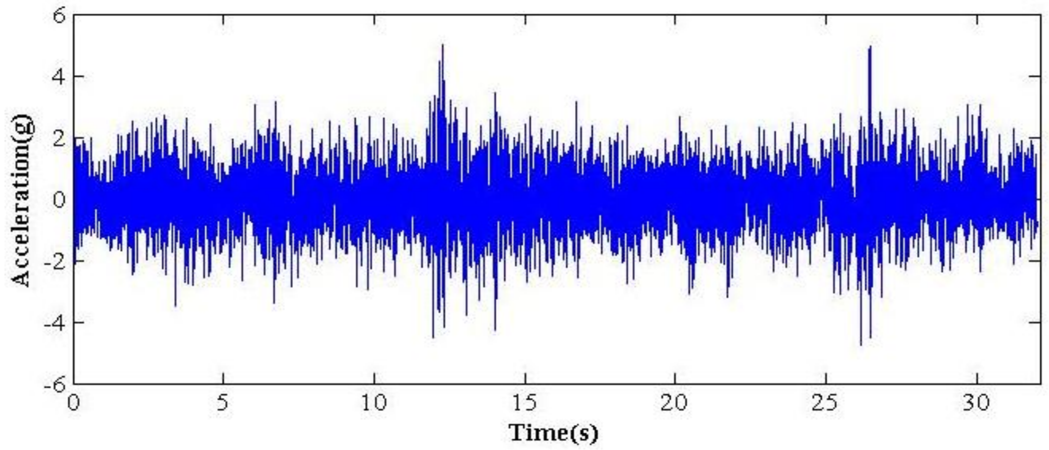
To apply the proposed method, 20 test measurements from the healthy state are accounted for a reference dataset (training phase) and 20 test measurements from each state (healthy state and 5 damage states) are considered as the current structural state (i.e., H, D1-D5). To determine the number of sources, the *I* indicator according to Eq. (9) is considered for m = 1, 2, …, 20. These values for each structural state in DOF 1 are shown in Table 5. Regarding *I* values, the numbers of sources are chosen as 19, 20, 20, 18, 20, 19, and 14 for R, H, D1, D2, D3, D4, and D5 states, respectively. In each state, the last source is considered an independent source. Choosing fewer sources makes the last source not independent enough and the more sources lead to the disappearance of some structural information. For example, if 19 sources in D2 is chosen and the 19th source is considered as an independent source, this source cannot express the behavior of the structure. Figure 7 demonstrates the last source in DOF 1 when the number of sources is 18 and 19.

The AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) are considered in order to determine a proper time series model. As an example, the ACF and PACF plot of the independent source in DOF 1 is shown in Figures 8 and 9. It can be seen that in Figure 8, the ACF approaches zero as time goes to infinity by damped wave sine and Figure 9 shows cut off at PACF.

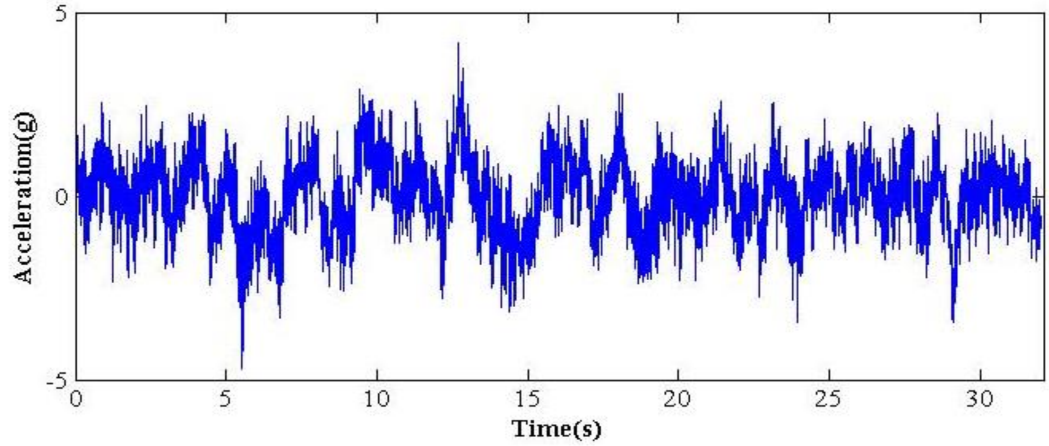
So, according to Box-Jenkins approach, the nature of this time series is an AR process and thus, according to what is explained in Section 2.2, the ARARX model is selected.

Table 5. The *I* indicator in DOF 1 for each structural states of wooden bridge

M Values	Structural states						
	R	H	D1	D2	D3	D4	D5
1	0.1173	0.0850	0.1032	0.1512	0.1021	0.1026	0.1483
2	0.1976	0.1648	0.1777	0.2353	0.1746	0.1772	0.2618
3	0.2746	0.2361	0.2447	0.3032	0.2463	0.2494	0.3691
4	0.3430	0.3065	0.3075	0.3692	0.3112	0.3100	0.4727
5	0.4095	0.3733	0.3687	0.4329	0.3725	0.3703	0.5658
6	0.4751	0.4381	0.4269	0.4927	0.4316	0.4263	0.6554
7	0.5393	0.4988	0.4816	0.5485	0.4876	0.4813	0.7242
8	0.6000	0.5580	0.5350	0.6024	0.5426	0.5339	0.7762
9	0.6553	0.6132	0.5878	0.6532	0.5945	0.5852	0.8258
10	0.7063	0.6664	0.6379	0.7014	0.6454	0.6349	0.8726
11	0.7539	0.7158	0.6852	0.7469	0.6935	0.6839	0.9187
12	0.7907	0.7626	0.7306	0.7900	0.7402	0.7315	0.9623
13	0.8269	0.8037	0.7747	0.8309	0.7846	0.7782	0.9999
14	0.8604	0.8384	0.8174	0.8703	0.8248	0.8223	1.0000
15	0.8924	0.8722	0.8587	0.9068	0.8630	0.8648	1.0000
16	0.9232	0.9043	0.8982	0.9409	0.8995	0.9050	1.0000
17	0.9532	0.9324	0.9336	0.9745	0.9341	0.9399	1.0000
18	0.9802	0.9588	0.9679	1.0000	0.9676	0.9711	1.0000
19	1.0000	0.9833	0.9999	1.0000	0.9999	0.9999	1.0000
20	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000



(a)



(b)

Fig. 7. The last source in DOF 1 when the number of sources is: a) 18; and (b) 19

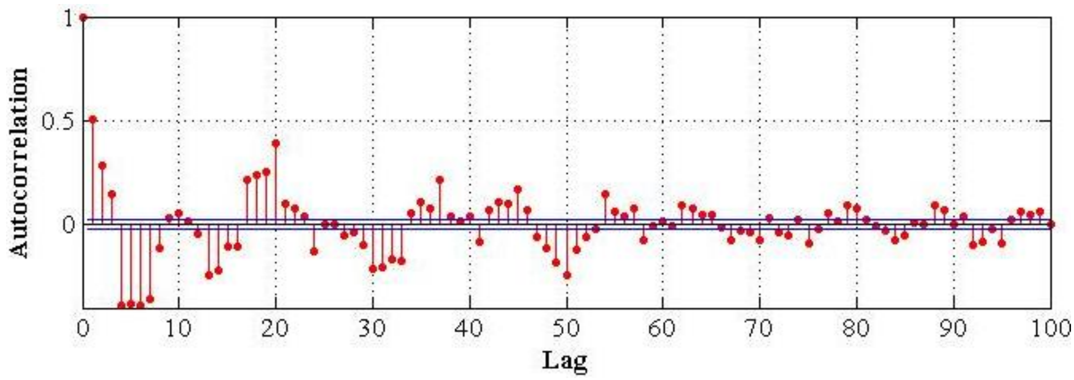


Fig. 8. The ACF plot of the independent source in DOF 1

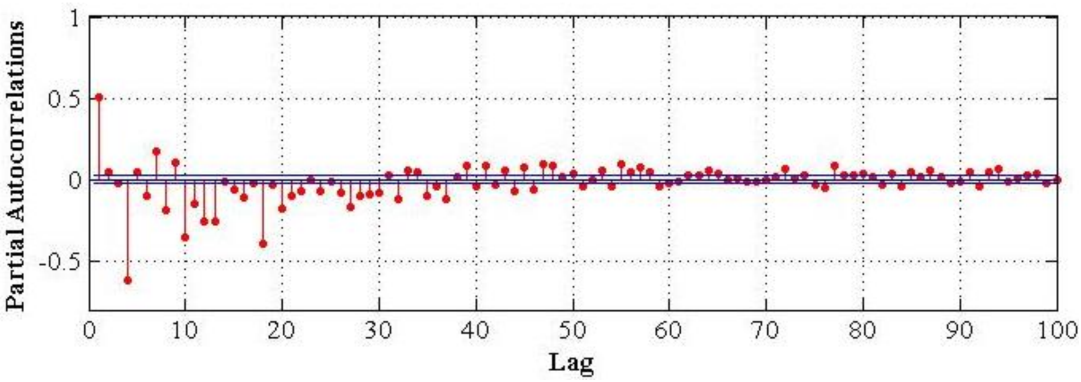


Fig. 9. The PACF plot of the independent source in DOF 1

The AR model order is estimated using the Akaike Information Criterion (AIC). For example, Figure 10 exhibits the AIC estimates in DOF 1. The optimal order is found to be 70, as shown in Figure 10. To determine the ARX model order, according to Ljung (1999) recommendation, the sum of α and β (ARX order) should be kept smaller than AR order p (i.e. $\alpha + \beta \leq p$). In this way, the ARARX model order is determined in each DOF and structural state.

As the structure is under the ambient vibrations, the acceleration data are supposed to be linear stationary signals. This assumption is examined by the ACF of the residuals of the ARARX model and is shown in Figure 11. The plot specifies no significant trend in the residuals and so the residuals are independent and identically distributed.

After specifying the ARARX model parameters in each DOF, the model is applied to the independent source in each structural state. Then, the Bhattacharyya measure is obtained between the residuals of the current state and reference state. To define the threshold value, a similar procedure as indicated in Section 4.1 is employed (Figure 12). A close look at Figure 12 reveals that the damage index in the health state in all DOFs is greater than the threshold limits. Also, it shows that between DOFs 4 to 6, which are in the same direction, DOF 4 has the lowest damage index. Similarly, between DOFs 10 to 12, DOF 10 has the lowest damage index. This localizes the damage which is near the sensors 4 and 10. Furthermore, in most DOFs, as the severity of damage increases, the Bhattacharyya measure decreases. In DOFs 13 to 15, there are some errors due to being away from the damage location; besides, all damage scenarios are small as mentioned earlier.

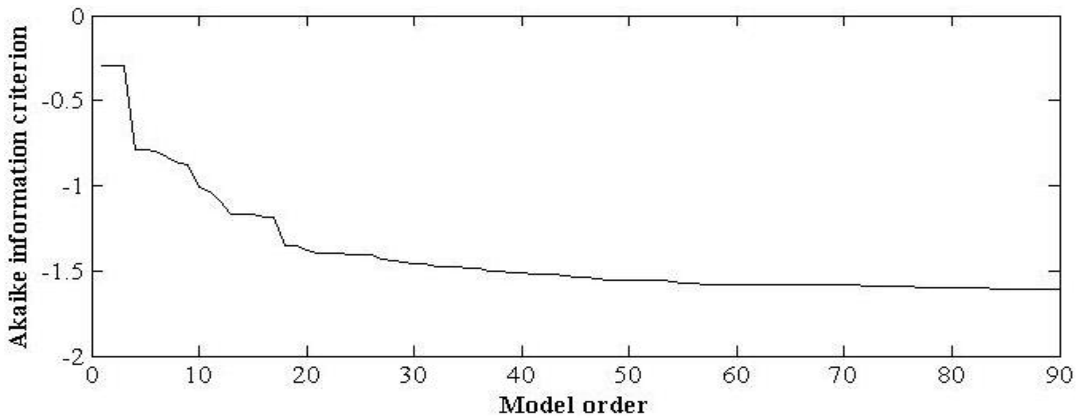


Fig. 10. Determination of the AR model order by the AIC method in DOF 1

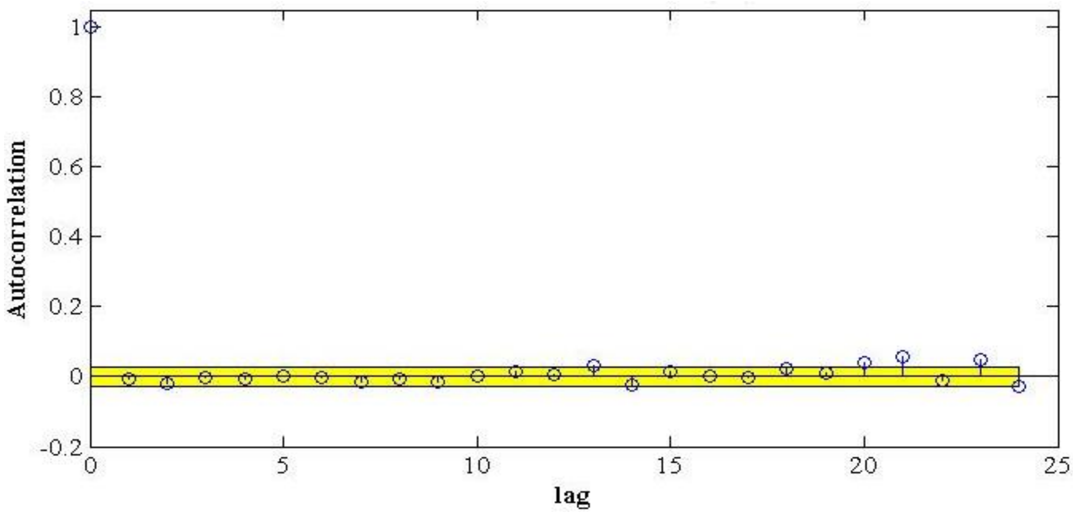


Fig. 11. ACF of residuals in DOF 1

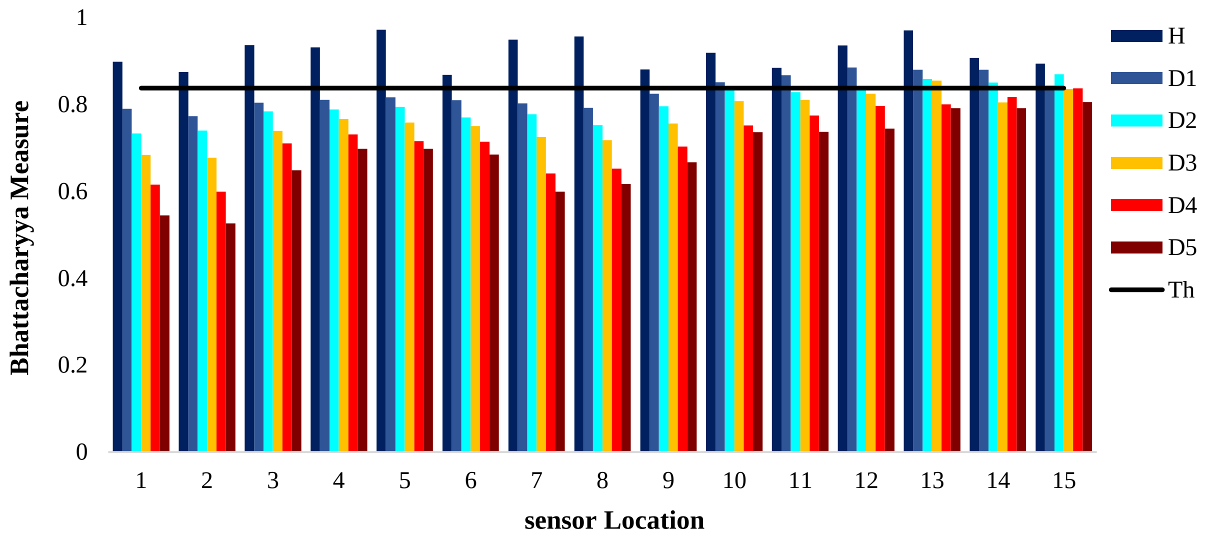


Fig. 12. The Bhattacharyya measure of odd DOF of beam structure in in each structural state

6. Discussion and Conclusion

In this paper, an innovative approach was proposed to detect and locate damage under the EOV conditions. In this approach, the ICA-based BSS approach was initially employed to acquire the time history response of the structure that is independent of unmeasured EOV. Then, time series analysis was applied to extract damage sensitive features. Finally, a novel statistical tool called Bhattacharyya measure was introduced to damage identification and localization using EOV independent features. The accuracy of the proposed techniques was validated by two useful benchmark structures under the simulated and actual EOV.

The first benchmark structure was a numerical beam structure under simulated EOV. The proposed method was applied to the acceleration measurements of the beam structure. Supposing normal distribution for Bhattacharyya measure in healthy state, the threshold value was defined. The damage index beyond the threshold value means that the structure is healthy and under that indicates a damaged state. Result showed that the proposed method could detect and localize damage. However, there were a few errors in results. Investigating the cause of errors revealsed that in all error cases, the indicator *I* was less than 0.97. It means that in these cases, the EOV effects have not been effectively eliminated and the obtained sources are not independent of EOV. Therefore, in these cases, more data measurements are needed in a relevant data set. The results showed as the damage severity increases, the damage index decreases; so the proposed approach could evaluate damage severity qualitatively. Furthermore, the proposed method was capable of damage localization even in the small damage scenarios. It showed that the proposed method was successful in early damage detection. As a result, if there are enough test measurements in each structural state, the proposed method can detect, localize damage, and evaluate damage severity qualitatively. Then a comparative study was conducted to indicate the capability of the suggested approach.

In this study, the structural state was analyzed based on the method proposed by Sohn and Farrer. The results showed that this method is also successful in damage diagnosis. However, the test measurements under EOV, which are needed in the training phase in the proposed method (10 test measurements), are much fewer than those in Sohn and Farrer's method (40 test measurements). Furthermore, the analysis time in the proposed method was about 12 times shorter.

The second benchmark structure was an experimental beam structure under actual EOV. In this beam structure, the steps of the proposed approach were considered in details. Firstly, the importance of proper estimation of the number of sources in BSS implementation was investigated. It showed that to determine the number of sources, the amount of *I* indicator should be considered. According to this study, the indicator *I* must be greater than 0.97. Furthermore, in the cases that with increasing the number of sources (m) the change in indicator *I* is negligible, the smallest m is chosen as the number of sources. Choosing fewer sources makes the last source not independent enough and the more sources lead to the disappearance of some structural information. Then, the process of determining the appropriate time series model and the order of chosen model was discussed in details. Finally, the results showed that although the damage severity was small, the proposed method was successful in damage detection and localization. It could also qualitatively evaluate the damage severity at the damaged area.

Based on the analysis of this study, it can be concluded that:

- The ICA-based BSS technique employed in the proposed method is effectively able to remove the EOV influence from the time history response of the structure under unmeasured EOV.
- The suggested approach uses a limited group of response data for extracting the independent damage-sensitive features in the training phase. This significant advantage grants the suggested approach, in comparison with the conventional approach, to be a more time-saving and effective tool for damage assessment of structures with reliable results.
- The introduced Bhattacharyya measure is a powerful tool in decision making for damage identification and localization. It can also qualitatively evaluate the severity of damage.
- The proposed method can be effectively employed in the issues of early damage identification.

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