Statistical Damage Detection Approach in SHM Based on Error Prediction Model

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***Abstract*—Vibration-based structure health monitoring technique detects the damage by observing the change in dynamic characteristics of the structure. Change in dynamic characteristics due to operational and environmental variation may confuse with the change due to damage in the structure resulting false alarm of the damage. In SHM, data normalization technique can be used to suppress the adverse effect due to different operational and environmental variability. In this paper, a data normalization approach based on error prediction model is presented that estimates the residuals of the vibration feature due to damage. Damage is detected by processing the residual errors after applying Principal Component Analysis (PCA) on vibration features. The residual errors due to operational and environmental variabilities are optimally minimized through the best reconstruction of vibration features using an optimal number of principal components. The Variance of Reconstruction Error (VRE) is applied to obtain the optimum number of principal components for best reconstruction of vibration features. Relative standard deviation of the residual errors is used as damage index that quantifies the level of the damage in the structure. The proposed approach is validated on a benchmark problem of detecting damage in a three-story building under different operational and environmental variabilities. A comparative analysis is performed with previously reported work for damage detection to test the efficacy of the proposed algorithm.**

***Index Terms*—auto-regressive model, principal component analysis, variance of reconstruction error, data normalization, damage index**

I. Introduction

In Structural Health Monitoring (SHM), anomalies detection in civil structures under varying environmental condition is a challenging problem. The change in vibration features is employed to detect the damage in the structure. The various operational and environmental variabilities have an influence on the dynamic characteristics of the structure. The change in vibration features under operational and environmental variations may have reduced the sensitivity to damage sensitive feature resulting false alarm [1], [2]. In SHM, the data normalization process is stated as the process of separating the change in the vibration feature due to operational and environmental variabilities from the changes due to damage on the structure. To address the issue, data normalization technique can be performed to eliminate the adverse effect due to varying operational and environmental condition from the vibration features [3].

Vibration responses of the structure are used for continuous monitoring of the structure. An advantage of these approaches is that no need to measure environmental parameters such as temperature, temperature gradient, humidity, etc. explicitly. In these approaches, operational and environmental variabilities are considered as implicitly embedded in structural response. In literature, few data normalization method have been proposed to address this problem. In last decades, researchers have proposed many algorithm for damage detection under varying operational and environmental conditions [4]-[7]. Figueiredo *et al.* [6] have discussed four different data normalization approaches based on machine learning algorithm for damage detection. They have compared four different machine learning algorithms for damage detection based on (i) Auto-Associative Neural Network (AANN), (ii) Factor Analysis (FA), (iii) Mahalanobis squared distance (MSD), and (iv) Singular Value Decomposition (SVD). They found that AANN and MSD based algorithms had better performance to detect damages compare to FA and SVD based algorithms when the safety of people will be the primary concern.

Yan *et al.* [8] have proposed a damage detection method for SHM under varying operational and environmental condition using Principal Component Analysis (PCA). They have used first six natural frequencies of the structure as vibration feature to detect damage in simulated 3-span bridge structure. The environmental effects are eliminated from the vibration features by discarding first few Principal Components (PCs) during the reconstruction of feature vectors. The selection of the number of principal components is

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crucial task in real-time application because the number of environmental effects and the source of unpredictable noise is not known beforehand. The vibration features which are more sensitive to damage that are also sensitive to varying operational and environmental conditions. In the SHM, it is desirable to have a damage sensitive feature that has to be correlated with the level of the damage in the structure. In literature, many SHM has used frequency response function, natural frequencies, mode shapes, mode shapes curvature, etc. as damage sensitive features. However, these features need to be extracted from vibration signal measured in a very controlled environment that is very difficult in real-time applications [4]. On the other hand, Auto-Regressive (AR) coefficients are extensively used as damage sensitive feature that are related to the natural frequencies and damping of the structure [9], [10]. Also, it is very easy to estimate the AR coefficients from the vibration signals.

In this paper, a data normalization approach with respect to various operational and environmental conditions is presented based on Error Prediction Model (EPM). EPM is developed using the vibration features extracted from the undamaged structural response. In this work, AR coefficients are used as vibration features to detect the damage in the structure. EPM uses the Principal Component Analysis (PCA) to minimize the residuals of the vibration feature employing an optimum number of Principal Components (PCs). The optimum number of PCs is selected based on best reconstruction criterion called Variance of Reconstruction Error (VRE) criterion. VRE criterion optimally divides the eigenspace in two optimal subspaces: Principal Component Subspace (PCS) and Residual Subspace (RS). After, modelling the EPM using undamaged vibration features, residual errors are estimated for all test feature vectors by eliminating the portion in PCS. The portion of vibration feature vector in PCS is eliminated to suppress the effect of operational and environmental variabilities. Relative standard deviation of the residual errors is used as damage index that quantifies the severity of the damage in the structure.

Rest of the paper is organized as follows. The estimation of AR coefficients as damage sensitive features is discussed in Section II. Section III describes the proposed algorithm for damage detection. The description of the vibration data used in damage detection process is described in Section IV. The validation of the proposed algorithm using collected vibration data is discussed in Section V. Finally; the paper is concluded in Section VI.

II. Damage Sensitive Feature Extraction

Vibration signals are collected from the multiple sensors placed on the structure to be monitored. Auto-regressive coefficients as damage sensitive features are estimated from the collected vibration data using AR model. A linear dynamic system can be modelled by using AR model that describes a time-varying process where current output series depends linearly on the previous value of the series. AR coefficients are extensively used as damage sensitive feature in many SHM applications [6], [10], [11]. The AR model of order d can be described as [12].

$$x(k) = \sum_{j=1}^{d} \phi_j x(k-j) + e_x(k) \tag{1}$$

where, $x(k)$ denotes the output sequence of the system in terms of previous output sequence and $e(k)$ random error of the model at k^{th} instance. ϕ_j corresponds to the j^{th} order AR coefficient. The unknown AR coefficients can be estimated using Yule-Walker equation or least square method. In this paper, least square method is adopted to estimate the AR coefficients from the vibration signal. The optimal order of the AR model described the dynamic behavior of structure uniquely. The optimal order of the AR model is obtained using Akaike Information Criterion (AIC) [12] discussed in Section V. AIC is a measure of the best fit of an estimated statistical model that is based on the trade-off between the number of estimated parameters. The AIC can be defined in the context of AR model as

$$AIC = N_t \ln(\varepsilon) + 2N_d \tag{2}$$

where, $\varepsilon = SSR/N_t$ the average sum-of-square residual (SSR) errors, N_d is the number of estimated parameters and N_t the number of predicted data points. To study the influence of autoregressive model order on damage detection, one may refer to [13]. The extracted damage sensitive features from the multiple sensors (mounted on the structure) are appended to form a dynamic characteristic feature vector. This feature vector uniquely defines the dynamic behavior of the whole structure.

III. Proposed Algorithm

The dynamic characteristic features are extracted from all the vibration signals collected from the undamaged and damaged structure. A training feature matrix, $X \in \Re^{m \times p}$, can be constructed using a p number of m dimensional vibration feature vector extracted from undamaged vibration data collected in p different operational and environmental conditions. The training feature matrix can be obtained as in (3).

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mp} \end{bmatrix} \tag{3}$$

where i^{th} column $x_i = [x_{1i}\ x_{2i} \cdots x_{mi}]^T$ of the training feature matrix X corresponds to the undamaged structural condition in i^{th} operational and environmental condition. However, test feature matrix $Z \in \Re^{m \times n}$ in (4) contains n feature vectors extracted from both undamaged and damaged vibration data.

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \cdots & z_{mn} \end{bmatrix} \tag{4}$$

where i^{th} column $z_i = [z_{1i}\ z_{2i} \cdots z_{mi}]^T$ of the test feature matrix Z corresponds to the unknown structural condition to be monitored. To construct an EPM, training feature matrix X is processed through PCA. PCA is a statistical procedure that allows us to identify the principal direction in which data varies. By suppressing those variations in vibration features, the various operational and environmental conditions can be suppressed.

PCA is applied to obtain a linear transformation of the training matrix X that can be decomposed into a score matrix T and a loading matrix P as given in (5).

$$X = P^T T \tag{5}$$

The columns of the matrix P represent the eigenvectors $p_1, p_2, \cdots, p_m$ corresponding to eigenvalues $\lambda_1, \lambda_2, \cdots, \lambda_m$ of the covariance matrix Σ. The principal components of X are the eigenvalues of the covariance matrix. Therefore, in this paper principal components and eigenvectors are used interchangeably. Here, the covariance matrix is defined as in (6) for zero-mean scaled X.

$$\Sigma = \mathbb{E}\{XX^T\} = P\Lambda P^T \tag{6}$$

where, $\Lambda = diag(\lambda_1, \lambda_2, \cdots, \lambda_m) \in \Re^{m\times m}$ is a diagonal matrix with eigenvalues arranged diagonally in decreasing order such that

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_l \geq \cdots \geq \lambda_m \geq 0 \tag{7}$$

It can be easily verified that $m-l$ eigenvalues of Σ are approximately equal to σ^2, that is,

$$\lambda_{l+1} \approx \lambda_{l+2} \approx \cdots \approx \lambda_m = \sigma^2 \tag{8}$$

$$and\ \lambda_i = \sigma^2 + \sigma_i^2\ \ for\ i = 1, 2, \quad , l \tag{9}$$

Therefore, it is assumed that change in the variance due to different structural conditions is equally distributed along all eigenvectors. Whereas, the effect due to various operational and environmental conditions influences the first l largest eigenvectors. Yan *et al*. [8] have suggested that first few eigenvectors corresponding to higher eigenvalue are significant for the change in vibration features due to various operational and environmental factors. Where the number of dominant eigenvectors corresponds to the number of environmental variabilities and unpredictable noise. In practical application, it is very difficult to anticipate the factors that influence the vibration features.

In SHM, the number of environmental parameters and unpredictable noise is very difficult to find if the structure is complex and exposed to the open environment. In this paper, the covariance-based Variance of Reconstruction Error (VRE) method is applied to determine the optimum value of l. Qin and Dunia [14] have proposed a new approach to determine the optimum number of eigenvector for the best reconstruction in the field of process control. The advantage of the VRE method is that it has a global minimum corresponding to best reconstruction. According to Qin and Dunia, the variance of reconstruction error in the direction of i^{th} eigenvector is defined as

$$u_i(l) = \mathrm{var}\left\{\xi_i^T (X - \hat{X})\right\} = \frac{\tilde{\xi}_i^T \Sigma \tilde{\xi}_i}{\left(\tilde{\xi}_i^T \tilde{\xi}_i\right)^2} \tag{10}$$

where

$$\tilde{\xi}_j = \left(I - PP^T\right)\xi_j = \tilde{P}\tilde{P}^T \xi_j \tag{11}$$

$\tilde{\xi}_i$ denotes the i^{th} column of identity matrix $I \in \Re^{m\times m}$. The variance of reconstruction error, u_i, need to minimize with respect to l. To obtain the optimum number of PCs, the VRE can be defined as

$$VRE(l) = \sum_{j=1}^{m} \frac{u_j(l)}{\mathrm{var}\left\{\xi_j^T X\right\}} = \sum_{j=1}^{m} \frac{u_j(l)}{\xi_j^T \Sigma \xi_j} \tag{12}$$

The variance based weighting factor is used to equalize the importance of vibration feature along each eigenvector.

To select the optimum number of PCs for best reconstruction, VRE procedure can be summarized as follow:

- Decompose the training feature matrix using PCA to find the eigenvector and corresponding eigenvalues.
- Reconstruct individual training feature vector using other training feature vector and calculate the VRE, u_i.
- Calculate the total VRE for all the eigenvectors using (12).
- Select the optimum number of PCs that gives the minimum VRE, which corresponds to the best reconstruction.

After finding the optimum number of PCs for best reconstruction, the test feature vector z_i is reconstructed using optimum number of PCs and residual errors e are computed as

$$e = z_i - \hat{z}_i \tag{13}$$

where z_i is the i^{th} column of the test feature matrix Z. $\hat{z}_i$ is the best-reconstructed test feature vector using the optimum number of eigenvectors of EPM. We observed that standard deviation of the residuals change drastically. Therefore, we have computed the relative standard deviation of the residuals as damage index (DI) that can be defined as

$$\mathrm{DI}(i) = \left|\frac{\sigma_i}{\mu_i}\right| \tag{14}$$

where, σ_i and μ_i are the standard deviation and mean of the residuals corresponding to i^{th} test feature vector respectively. The DI defines the extent of damage in the structure.

IV. Data Description

The efficacy of the proposed algorithm is tested using experimental vibration data collected from Los Alamos National Laboratory website available publicly for experimental evaluation [15]. The three-story frame structure consists of columns and plates assembled using bolted joint as shown in Fig. 1.

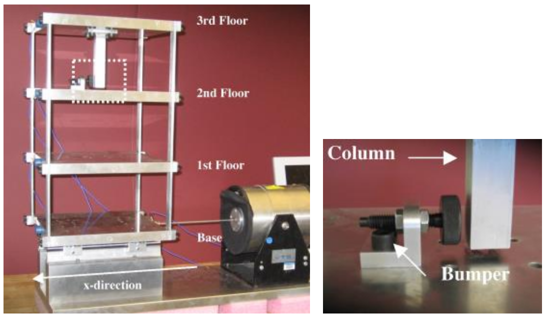


Figure 1. Three story building [15].

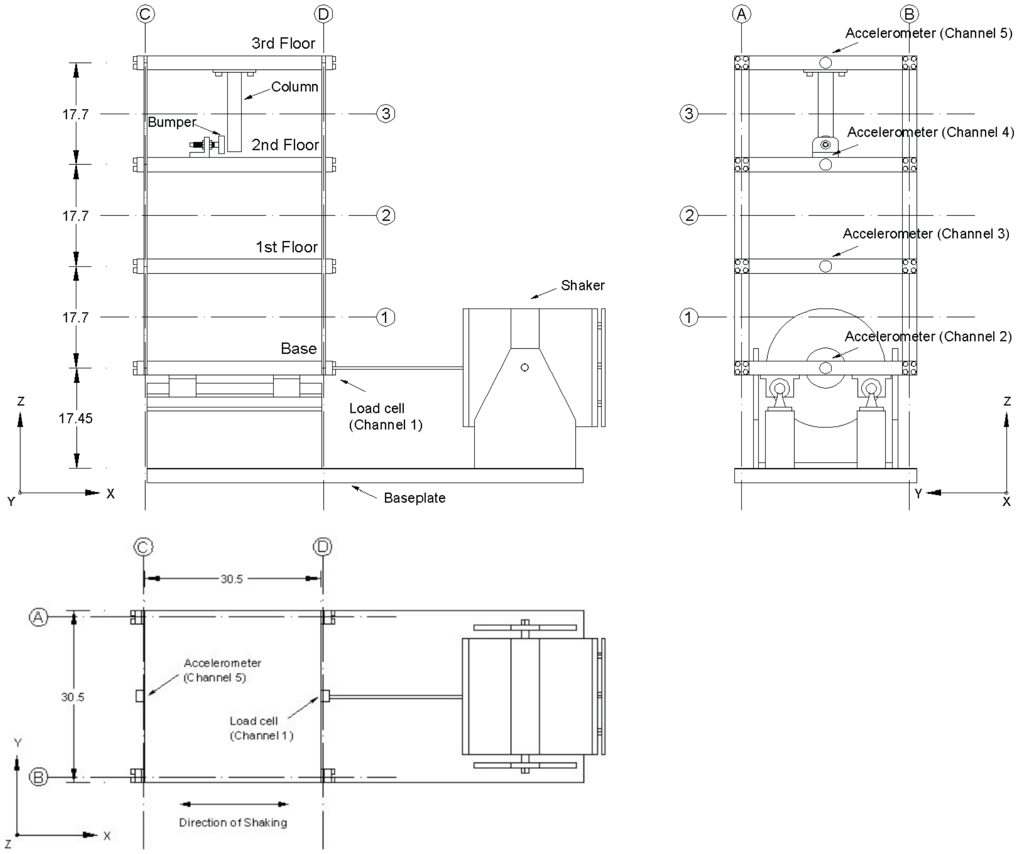


Figure 2. Three story frame with basic dimensions (all dimensions are in cm) [15]

The dimensions of the three-story frame structure are shown in Fig. 2. For more detail about the geometry of the structure and excitation to the structure for the data collection, one may refer to [6]. The whole structure is modelled to emulate a breathing crack in the structure under various operational and environmental conditions. Additionally, a center column was suspended from the middle of the top floor to introduce a non-linear behavior of the structure when the column contacts a bumper mounted on the next floor. The gap between the bumper and the center column denotes the level of damage introduced in the structure that corresponds to the width of the breathing crack. The different operational and environmental conditions are emulated through reducing the stiffness of the various columns and adding mass at different floors. The stiffness of columns is reduced by means of replacing that column with a column having half area of cross section. Various state conditions with level and description are given in Table I. Nomenclature for column 1AD corresponds to column of first floor intersecting plane A and D. A, B, C, and D correspond to four faces of the three-story frame structure. Similarly, other nomenclatures are used.

Structural state condition described in Table I are classified in four groups. State#1 is categorized in the first group that indicates the baseline condition of the structure. The second group of state condition consists of State#2-State#9 that are collected from the undamaged structure under various operational and environmental conditions. The operational and environmental variabilities are emulated through reducing stiffness and adding mass-load at various location of the structure. Various level of damages were introduced in the structure with the help of bumper and center column to simulate State#10-State#14 (third group). Varying the gap between bumper and center column controls the level of damage.

A Higher value of the gap corresponds to the low level of damage whereas smaller gap corresponds to a high level of damage. In the last group, to consider the more realistic state conditions, damages were simulated in addition to the mass and stiffness changes to consider the operational and environmental variabilities (State#15-State#17).

TABLE I. STRUCTURE STATE CONDITION WITH DESCRIPTION

Label	State Condition	Description
State#1	Undamaged	Baseline condition
State#2	Undamaged	Added mass (1.2 kg) at the base
State#3	Undamaged	Added mass (1.2 kg) on the 1st floor
State#4	Undamaged	Stiffness reduction in column 1BD
State#5	Undamaged	Stiffness reduction in column 1AD and 1BD
State#6	Undamaged	Stiffness reduction in column 2BD
State#7	Undamaged	Stiffness reduction in column 2AD and 2BD
State#8	Undamaged	Stiffness reduction in column 3BD
State#9	Undamaged	Stiffness reduction in column 3AD and 3BD
State#10	Damaged	Gap (0.20 mm)
State#11	Damaged	Gap (0.15 mm)
State#12	Damaged	Gap (0.13 mm)
State#13	Damaged	Gap (0.10 mm)
State#14	Damaged	Gap (0.05 mm)
State#15	Damaged	Gap (0.20 mm) and mass (1.2 kg) at the base
State#16	Damaged	Gap (0.20 mm) and mass (1.2 kg) on the 1st floor
State#17	Damaged	Damaged & Gap (0.10 mm) and mass (1.2 kg) on the 1st floor

V. RESULTS AND DISCUSSION

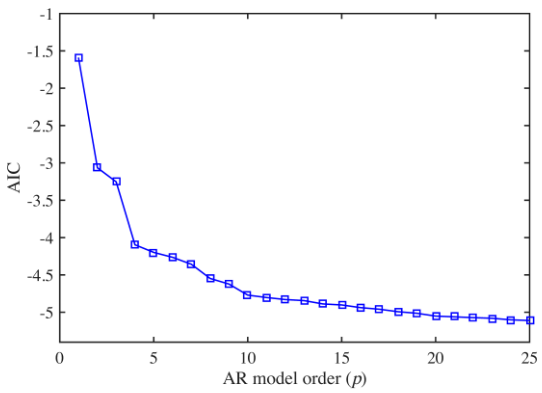


Figure 3. Average AIC value for different order of AR model.

In this section, the proposed algorithm is validated using dynamic characteristic features extracted from the vibration data as described in the previous section. AR coefficients are used as dynamic characteristic features for damage diagnosis. Each state condition were emulated for 100 times resulting 900 undamaged data (state#1-State#9) and 800 damaged data (state#10-State#17). The training dataset contains 50 undamaged data selected randomly from each undamaged state. Remaining 450 undamaged structural states and 800 damaged structural states are used for testing purpose. Dynamic characteristic features are extracted from structural responses collected from four accelerometers placed on each floor (shown in Fig. 2). Optimal order of AR model is selected based on Akaike Information Criterion (AIC) value. The average AIC value of 100 baseline conditions (State#1) is obtained for the different order of AR model in the range of 1-25. From Fig. 3, it can be observed that there is no significant change in the AIC value after 10^{th} order AR model. Therefore, optimal order of the AR model is selected as 10. The vibration features, extracted from all four channels, are appended resulting in a 40-dimensional feature vector. Training matrix $X \in \Re^{40\times 450}$ is constructed using 450 undamaged 40-dimensional vibration feature vectors. Remaining, vibration feature vectors corresponding to undamaged and damaged structural condition constitute a test feature matrix $Z \in \Re^{40\times 1250}$.

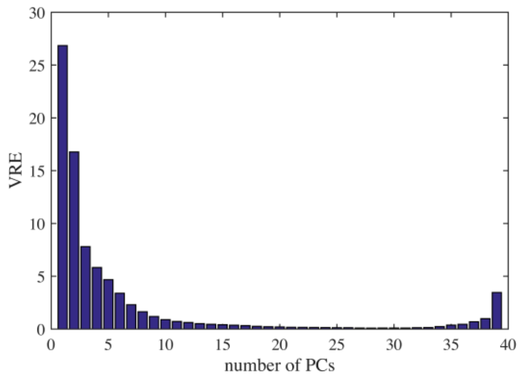


Figure 4. VRE vs. number of PCs.

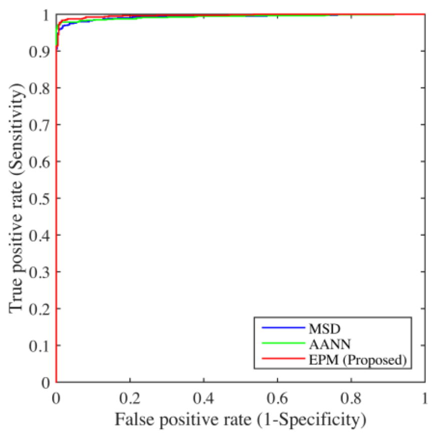
Error prediction model is developed using training matrix after applying PCA. Using PCA, the eigenvectors are calculated from the covariance matrix $S \in \Re^{m\times m}$ of the training matrix X . The obtained eigenvectors constitute an eigenspace that can be divided optimally into two subspace called Principal Component Subspace (PCS) and Residual Subspace (RS) using VRE. The portion in PCS has a tendency to increase with the number of PCs, and that in the RS has a tendency to decrease, resulting in a minimum in VRE [16]. The optimum number of PCs is obtained by selecting a number of PCs corresponding to minimum VRE. The optimum number of PCs can be used to reconstruct the vibration feature vector to predict the residual error. The VRE for the different number of PCs is plotted in Fig. 4.

For the EPM of training matrix, the optimum number of PCs is obtained at $l = 29$ for best reconstruction of the training feature vectors. Therefore, all test feature vectors are reconstructed using first 29 PCs of the training matrix, and residual errors are calculated. It was observed that mean of the residual errors varies significantly. Therefore, the coefficient of variation that is the ratio of the variance to the mean of residual error is considered as damage sensitive index.

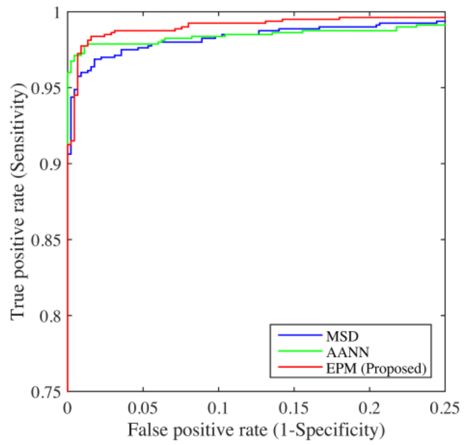
The proposed damage detection technique is compared with earlier reported damage detection method based on AANN [17] and MSD [18]. AANN based damage detection approach trains the network to realize the non-linear PCA to learn the correlation between the vibration features of the training matrix X. The non-linear PCA is used to perform identity mapping employing AANN where the network tries to reproduce the input at the output with minimum error. If the input feature vector corresponds to the undamaged structure condition, then the network is able to reproduce the feature at the output with minimum error. On the other hand, if the input feature vector corresponds to the damaged structure then reproduction error will increase significantly. The more detail about the architecture of the AANN for damage classification under varying operational and environmental condition can be found in the reference [17]. Another most adopted damage detection approach is based on Mahalanobis square distance. In MSD based data normalization approach [10], [18], Damage index of any test feature vector z_i is defined as:

$$DI(i) = (z_i - \bar{x})^T \Sigma^{-1} (z_i - \bar{x}) \tag{15}$$

where, $\bar{x}$ and $\Sigma \in \Re^{m \times m}$ are mean vector and covariance matrix of training matrix X. The DIs corresponding to all test feature vector using MSD, AANN and proposed methods are calculated. For the better comparison, Receiver Operating Characteristic (ROC) curves for MSD, AANN, and proposed technique are plotted in Fig. 5.



(a)



(b)

Figure 5. ROC curve for each algorithm: (a) linear scale, (b) zoomed to highlight the difference between curves.

ROC curve represents the performance of the binary classifier where the True Positive Rate (TPR) is plotted against False Positive Rate (FPR) for various threshold values. The perfect classification will be obtained if the ROC curve approaches to top left corner of the ROC space. From Fig. 5, it can be observed that ROC curve corresponding to proposed algorithm is closest to (0, 1) coordinate of the ROC space compare to other approaches. It shows that proposed technique has better classification performance compared to other methods. In SHM, Type I (False negative) and Type II (False positive) errors are used to test the capability of the damage detection approaches. Type I error is related to the maintenance cost whereas the Type II error corresponds to the safety. To find the Type I and Type II error, a threshold value is decided based on the 98 % cut-off value over training data. Table II summarizes the number of Type I and Type II error in terms of the number of data sample for each algorithm.

It can be observed that proposed algorithm outperforms over MSD- and AANN-based damage detection approaches in terms of Type I and Type II error. The overall performance of the proposed technique is obtained 98.32 \%.

TABLE II. NUMBER OF TYPE I AND TYPE II ERROR

Algorithm	Error		
	Type I	Type II	Total (in %)
MSD	78	8	86 (93.12)
AANN	33	14	47 (96.24)
EPM (proposed)	8	13	21 (98.32)

The DI for the all test feature vectors with the threshold are plotted in Fig. 6. The calculated DIs are plotted along Y-axis vs test sample number on X-axis. The DIs corresponding to first 450 test samples is for undamaged vibration data represented by blue dots. The DIs corresponding to remaining 800 test samples is for damaged vibration data represented by red dots.

It can be observed that DI corresponding to undamaged structural condition using MSD-and AANN-based approaches has more variations compare to proposed algorithm that shows that proposed model is more efficient to nullify the operational and environmental effect from the vibration features. It is already stated that DI has to be a linear relationship with the level of damage. Here, the level of damage is defined as the gap between the bumper and center column (depth of the crack). It will be worth to note that DI obtained through MSD-and AANN-based approaches not varying linearly with damage level under various operational and environmental condition. Whereas, DI has a linear relationship with the level of damage using proposed algorithm.

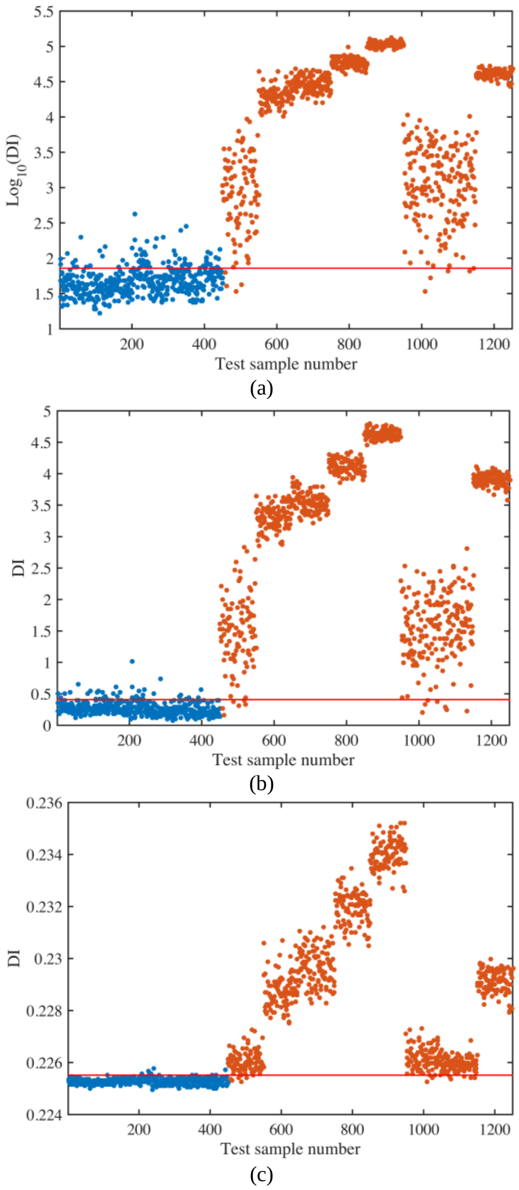


Figure 6. Damage detection using three different approaches with threshold value. Blue dots and red dots correspond to the DIs for the undamaged and damaged structure conditions.

VI. Conclusion

Error prediction model based data normalization technique under varying operational and environmental condition has been proposed. The proposed technique computes the residual error based on the variance of reconstruction error criterion. An optimum number of principal components for best reconstruction of vibration features are obtained through VRE criterion. The relative standard deviation of the residual error is found to be a damage sensitive index that has the linear relationship with the level of damage. The proposed algorithm is validated using the standard vibration data of the three-story frame structure and compared with earlier methods used for data normalization in SHM. The EPM-based approach for damage detection assigns a consequential damage index to the different level of damages. Proposed technique reduces the Type II error along with Type I error to reduce the maintenance cost and increases the reliability of the structure. Therefore, the proposed technique can be used for damage detection in real-time application under varying operation and environmental conditions.

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