Vibration-based damage detection of structural joints in presence of uncertainty

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Abstract. Early damage detection of structure's joints is essential in order to ensure the integrity of structures. Vibration-based methods are the most popular way of diagnosing damage in machinery joints. Any technique that is used for such a purpose requires dealing with the variability inherent to the system due to manufacturing tolerances, environmental conditions or aging. The level of variability in vibrational response can be very high for mass-produced complex structures that possess a large number of components. In this study, a simple and efficient time frequency method is proposed for detection of damage in connecting joints. The method suggests using singular spectrum analysis for building a reference space from the signals measured on a healthy structure and then compares all other signals to that reference space in order to detect the presence of faults. A model of two plates connected by a series of mounts is used to examine the effectiveness of the method where the uncertainty in the mount properties is taken into account to model the variability in the built-up structure. The motivation behind the simplified model is to identify the faulty mounts in trim-structure joints of an automotive vehicle where a large number of simple plastic clips are used to connect the trims to the vehicle structure.

1 Introduction

Joints such as clips and bolts are commonly used in the built-up structures to connect different components. The damage in these joints can adversely affect the integrity of the whole structure and may lead to catastrophic incidents. Thus, an early detection of damage in the structure with faulty joints is crucial in order to maintain the safety and to extend the service life span of structures.

Damage detection in structural joints has attracted a lot of attention and many techniques were developed during the past few decades. Vibration-based analysis is one of the most popular strategies for the damage detection as it is non-destructive and repeatable. The deviation of natural frequencies and damping ratios from the baseline values due to bolt looseness is investigated in [1] where a couple of Euler beams with a single bolted lap joint is used in the analysis. The results illustrate that the bolts looseness affect the structure's natural frequencies and damping ratios. However, the change is more significant at the higher frequency range.

In reference [2], an experimental investigation is conducted for identifying the looseness in cargo bolts under random excitation. The experiment is conducted on twelve bolt groups and seven different severity of damages (i.e. looseness). For each simulated damage type, vibration signals are acquired using accelerometers and time series are used for detection. Two kinds of autoregressive models were constructed. The residual errors of the models are used as damage index for different levels of damage. The results showed that the suggested methodology has the possibility of early detection of bolt looseness severity.

A damage detection method based on the analysis of the subharmonic resonance is presented in [3]. The study proposed the structure bolted joint as a two-degree of freedom nonlinear model and uses a multiple timescale method for illustrating the generation of subharmonic resonance. Experiments were conducted on a single bolt-joint aluminum beam and the damage in the joint is simulated by bolts looseness. The excitation of the beams and acquisition of the corresponding response signals are conducted by piezoelectric transducers. The results showed that the subharmonic frequencies appear in the structure response spectrum when it is excited by a double of its natural frequency.

The study in [4] presents a technique for the looseness detection of bolted structure. The technique based on the frequency response function (FRF) data. The experimental results of the study are obtained using both accelerometer and strain gauge and their measurements are compared to assess the bolt looseness. The results show that presence of bolt looseness causes and abrupt change in the orthogonal modes.

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The detection of undesired structural changes in space vehicle due to bolt looseness is investigated in [5]. Special kind of piezoelectric sensors are used on a real satellite panel with 49 bolts. The damage in the satellite panel is simulated as looseness in a bolt. The capability of two different methods, namely Acousto-Elastic and Electro-Mechanical Impedance methods, of detecting damage is investigated. The experimental results of the study show that the present techniques have a potential possibility for both damage detection and localization.

A combined methodology based on vibration and electro-mechanical impedance techniques for the purpose of structural joint damage detection is presented in [6]. A number of structure joint damage scenarios are designed in the study for the purpose of damage detection. The experimental results such as modal parameters are analyzed and showed that the present methodology is useful in extracting damage information of the joint.

The study in Ref. [7] proposes an artificial neural network (ANN) based method for the estimation of damage severities in truss bridge's joint. The mode shapes and natural frequencies are used as input features to the ANN in order to assess the damage. A numerical analysis is presented in order to assess the method's efficiency and accuracy.

In this study, the effectiveness of a new method to detect the damage in joints of two connected plates is investigated. The uncertainty in joint property are modelled using the measured variability of plastic mount that are used to connect the trim to the structure of an automotive vehicle [8]. A large number of these clips are used in modern vehicles. These clips should be firmly connected and any rattling can be a source of unwanted noise in a vehicle's cabin. It is shown that the variability in the effective stiffness and damping of such clips can affect the vibration response of the vehicle [8]. Such variability makes the damage detection process more difficult and uncertain.

A simple and easy methodology based on Singular Spectrum Analysis (SSA) is suggested here for damage detection. In this method, the time domain vibration acceleration signals are subjected to the SSA for the decomposition purposes. From the response of structure with healthy joints a reference space is made. Other signals of the healthy structure will be projected onto this space and allow an estimation of a threshold value. Any new signal will be projected on that baseline space and their distance to the cluster of healthy signal will be compared to the threshold value to classify them as healthy or damaged.

In the following section, the mathematical formulation of the problem is described. In section 3, the fundamentals of the SSA are described briefly. Results and discussion are presented in section 4 and the section 5 focuses on conclusions made in this paper.

2 Mathematical formulation of the problem

A simple model of two connected steel plates with multiple mounts is used here in order to simulate a built-up structure. For the purposes of modeling, the steel plates are simply supported and thus an analytical solution for their vibration response exists according to Kirchhoff–Love plate theory [9]. The two plates are connected by eleven mounts which are distributed randomly between the plates. This allows obtaining an analytical solution using the impedance-mobility technique (FRF coupling) [10,11] The plates are made of steel and have the following dimensions: plate 1 has a thickness of 1.5 mm, width of 350mm and length of 500mm; plate 2 has a thickness of 1.3mm, width of 400mm and length of 600mm. A schematic view of two plates is shown in figure 1. The mobility functions between point 1 on the first plate and point 2 on the second plate are obtained.

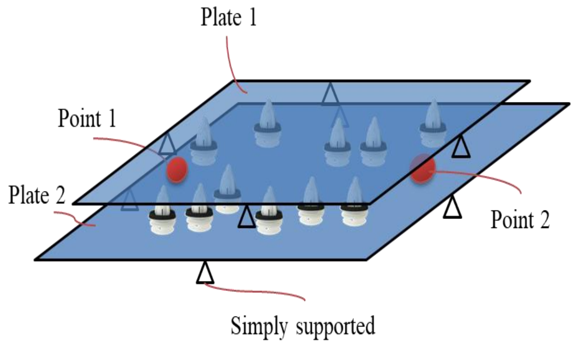

Fig. 1. A schematic view of two plates connected by eleven clips.

The uncertainty in the clips properties are considered based on the measurement conducted in [8]. A Monte Carlo simulation is used to obtain the point and the transfer mobilities while the clips properties are varied. The mobility Y_{12} for point 1 of the first plate and point 2 of the second plate is shown in figure 2 for 250 realisations where all clips are considered connected. It can be seen that at lower frequencies there are distinct modes which are not affected by the variability in clips properties. However, the effect of variability in the clips properties becomes more prevalent with the increase of the frequency.

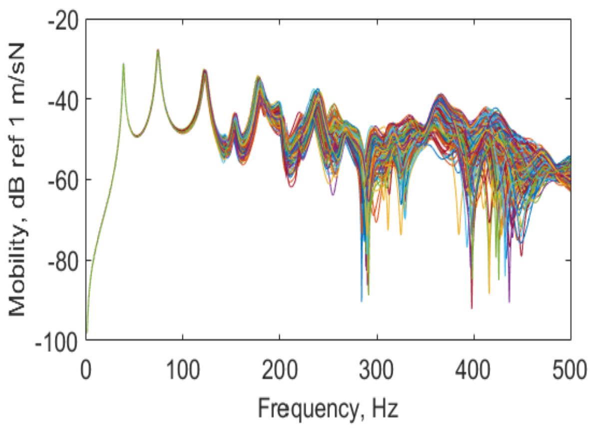

Fig. 2. Monte Carlo simulation results of mobility Y_{12} of two connected plate with 11 clips.

Damage is modelled by removing one clip at a time. Then again, a Monte Carlo simulation is used to simulate the effect of uncertainty in the clip properties. The mobility Y_{12} for the two connected plates, where one of the clips is removed is shown in figure 3. Here, again 250 realisations for each case are produced. Overall 11 cases of damaged joint and one case with no damage are presented in figure 3. The variability in the clips properties make it impossible to distinguish between each case and there are overlap between healthy and damaged connector for all the cases.

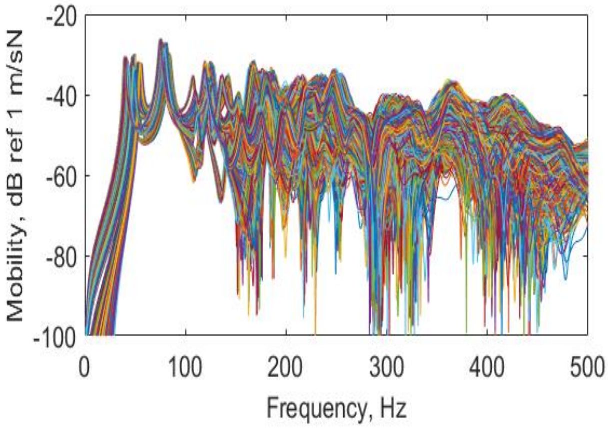

Fig. 3. Monte Carlo simulation of the mobility Y_{12} of two connected plate for healthy and damaged connections where one of the clips is removed each time.

3 Methodology

SSA is a time series analysis method that popularly used in biomedical and meteorological sciences [12-14]. Recently, it was used for the purposes of engineering application such as fault diagnosis of rolling element bearings [15-19], tool wear health monitoring [20, 21] and delamination in composite materials [22].

The SSA has two main stages; decomposition and reconstruction. In the first stage, a signal which is discretized as a time series is decomposed into a number of independent components, the principal components (PC's). Each component contains a certain percentage of the original signal variance. The reconstruction stage, which is not used in this methodology, uses all or some of the principal components to reconstruct the original signal. Further details of the SSA can be found in [23, 24].

The methodology suggested has two key steps: building baseline space and damage detection methodology. The later contains extraction of feature vectors (FVs), setting a threshold and a classification process.

3.1 Building reference/baseline space.

A baseline space is made from subjecting a signal measured on a healthy structure to the decomposition stage of the SSA. First a trajectory matrix **X** of dimension L by K is made from the time-lapped signal x of a length n (i.e $x = [x(1), x(2), x(3) \ldots x(n)]$) as shown in Eq. (1):

$$\mathbf{X} = \begin{bmatrix} x(1) & x(2) & x(3) & \cdots & x(K) \\ x(2) & x(3) & x(4) & \cdots & x(K+1) \\ x(3) & x(4) & x(5) & \ddots & x(K+2) \\ \vdots & \vdots & \vdots & & \vdots \\ x(L) & x(L+1) & x(L+2) & \cdots & x(K+L-1) \end{bmatrix} \quad (1)$$

where $x(n)$ is a n^{th} element of the measured signal. The L is the window of decomposition (i.e the number of PCs resulted from the decomposition stage) and K=n-L+1.The covariance matrix of the trajectory matrix can be obtained using to Eq. 2,

$$\mathbf{C}_{\mathrm{x}} = \frac{\mathbf{XX}'}{L} \quad (2)$$

Eigenvalues and eigenvectors of the covariance matrix $\mathbf{C_x}$ can be obtained by subjecting it to singular value decomposition,

$$\mathbf{C_x U}_i = \lambda_i \mathbf{U}_i \quad (3)$$

Each eigenvalue (i.e. λ_i) represents a fraction of the original signal's variance in the direction of the corresponding eigenvector $\mathbf{U}_i$. The eigenvalues are usually arranged in a decreasing order and the corresponding variances are represented in the so-called scree plot [25].

For building the baseline space, all or only a part of eigenvectors obtained above, which correspond to the healthy condition can be used.

3.2 Damage detection methodology

After building the baseline/reference space from a healthy signal, any new signal will be projected on the baseline space and the fault detection process is conducted. The detection process has two main steps: feature vector extraction and classification.

3.2.1 Feature vector extraction

Supposing signals from healthy and faulty condition are available, the healthy signals are divided equally into training and testing samples, while all the faulty signals are used as testing samples.

For the training samples, the trajectory matrix of every signal is projected onto the baseline space. The projection means multiplying the transpose of the trajectory matrix **X** by each of the baseline eigenvector $\mathbf{U}_i$. This projection will provide the corresponding principal components $\mathbf{PC}_i$,

$$\mathbf{PC}_i = \frac{\mathbf{X}'\mathbf{U}_i}{\lambda_i} \quad (4)$$

The symbol ($'$) denotes the transpose. Then, the Euclidean norm of each of the three principal components is calculated as in Eq.5,

$$f_{ij} = \sum_{m=1}^{K} \left(\mathbf{PC}_{ij}\,(m)\right)^2 \quad (5)$$

where f_{ij} is the feature, i is the number of principle component and j is the number of the signal that is projected.

In the present study, the baseline space is basically made from the first three eigenvectors. Hence, all feature vectors will be of three dimensions. More eigenvectors can also be used but in this study the first three vectors were sufficient to achieve a very good classification . Then the feature vector (FV) obtained from j^{th} signal will have the form,

$$\mathbf{f}_j = [f_{1j}\ f_{2j}\ f_{3j}]' \qquad (6)$$

The reason for choosing three feature components only is that these can be visualized in a 3D space.

3.2.2 Classification

When a baseline space is made and the training samples are projected, the resultant FVs are arranged in rows to form the baseline feature matrix $\mathbf{F}_{baseline}$. Then, the Mahalanobis distance (D_i)of each feature vectors to the $\mathbf{F}_{baseline}$ is calculated,

$$D_i = \sqrt{(fv_i - E_{baseline}).S^{-1}.(fv_i - E_{baseline})^T} \qquad (7)$$

Where $\mathbf{E}_{baseline}$ is the mean of the rows of the $\mathbf{F}_{baseline}$ and S^{-1} is the inverse of the covariance matrix of $\mathbf{F}_{baseline}$.

From the values of D_i corresponding to the baseline training sample a suitable probability distribution is fitted. In the present study, a lognormal probability distribution if fitted. From this probability distribution, a suitable threshold T_r is found. The threshold here is selected in a way the cumulative probability distribution become equal to 0.99 [26]. A new signal will be classified based on its D_i to the class of healthy or faulty signals, according to Eq. (8).

$$\begin{array}{ll} D_i > T_r & singal\ is\ assigned\ to\ healthy\ class \\ D_i \le T_r & signal\ is\ assigned\ to\ faulty\ class \end{array} \qquad (8)$$

where D_i is the Mahalanobis distance of i^{th} signal measured from the healthy space and T_r is the calculated threshold.

4 Results and discussion

As was mentioned in Section 3, 250 realisations were obtained for the case when all clips are connected that is for the case of healthy clips. Similarly, 250 signals are simulated for each case when one clip is removed. In total, there will be 3000 realisations (250*12 (1 Healthy case +11 removed clip cases)). The signals from the healthy structure are divided equally (i.e. each is 125 realisations) into training and testing samples, each one containing 125 signals. All the other 2750 signals are used as testing samples.

Figure 4 represents the 3D visualization of training FVs which were obtained according to Eq.6.

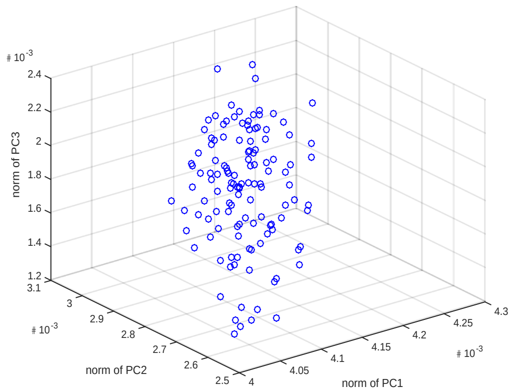

Fig. 4. 3D visualisation of baseline FVs.

Figure 5 shows the projection of the testing FVs on the baseline feature space. The healthy training and testing FVs are represented in blue color. The FVs corresponding to faulty class are represented in red color. It can be seen that the testing FVs corresponding to the faulty cases can be visually recognized from the baseline FVs.

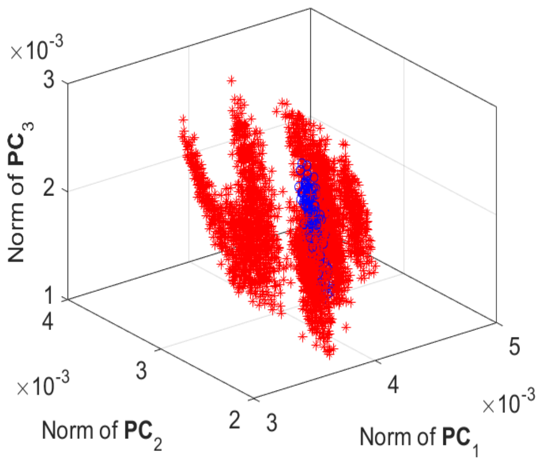

Fig. 5. Clustering of 3D visualisation of baseline FVs.

Figure 6 represents the Mahalanobis distances of all the feature vectors that were measured to the training FVs. The horizontal dashed line represents the threshold *Tr*. The figure clearly shows that the *D* level of the faulty FVs is higher than the *D* level of the training FVs. In this sense, the FVs made from faulty class are dissimilar to those made from training FVs. The FV's from the faulty class will be recognized as such according to the rule defined in Eq. (8).

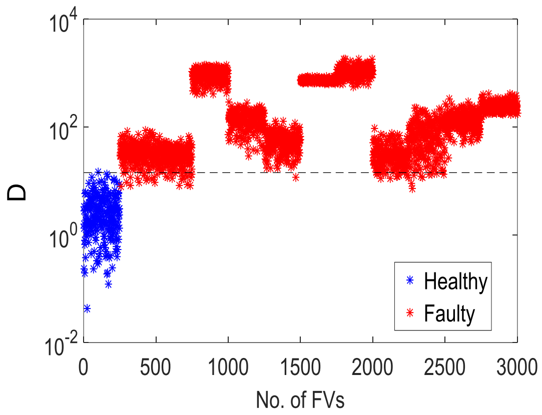

Fig. 6. The levels of *D* for both training and testing sample.

Table 1 shows the confusion matrix that represents the rates of correct and incorrect classification in percentages for the healthy and the faulty signals. The first column denotes the real class and the first row corresponds to the recognized class. The numbers on the main diagonal shows the correct classification rates while the off-diagonal numbers show the percentage of misclassified signals. All the 125 healthy FVs from the testing samples are correctly assigned to the healthy class. Only 31 out of the 2750 (1.13 %) testing FVs corresponding to faulty conditions were misclassified as healthy while all the rest 2719 FVs (i.e. 98.87%) were correctly classified as faulty.

Table 1. Confusion matrix

Real class/recognized class	**H**	**F**
H	100%	0%
F	1.13%	98.87%

5 Conclusions

This study suggests a vibration-based monitoring method to identify damage in joints in presence of variability. The proposed method is used to detect damage in a faulty joint of two connected plates. Two plates are assumed to be connected by small plastic clips that are used to connect the vehicle's trim to its structure. The variability in clips' effective stiffness and damping are modelled here using a Monte Carlo simulation.

The methodology proposed here does not require previous measurements of signals corresponding to faulty cases. The results obtained in the paper demonstrate the accuracy of the method, which supports the claim of using it for purposes of automatic damage assessment.

References

1 A. Dekal, A. Rao1, S. Kamath, A. Gaurav, K. Gangadharan, presented at the 2nd Mechanical Engineering Graduate Research Symposium (MEGRES), IIT Bombay, Mumbai, India (2015).

2 G. Dong, F. Zhao, and X. Zhang, Adv. Mech. Eng., **9**(3), 1-12 (2017).

3 M. Zhang, Y. Shen, L. Xiao, and W. Qu, Nonli. Dyn., **88**, 1643-1653 (2017).

4 H.C. Eun, Y.J. Ahn and S.G. Lee, "Experimental study on damage detection at bolted joint using frequency response function." in ACEM14, Busan, Korea, (2014).

5 D. Doyle, A. Zagrai, and B. Arritt, "Bolted joint integrity for structural health monitoring of responsive space satellites," in *the Proceeding of 50th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference,* Palm Springs, CA (2009).

6 W. Na, J. Lee, J. Kim, and D. Hong, "Hybrid Health Monitoring for Damage Detection in Structural Joints," (2006).

7 M. Mehrjoo, N. Khaji, H. Moharrami, and A. Bahreininejad, Exp. Sys. Appl., **35**, 1122-113 (2008).

8 A. Abolfathi, D. J. O'Boy, S. J. Walsh, A. M. Dowsett, and S. A. Fisher, Proc. IMechE, C: J Mech. Eng. Sci., 0954406217721724 (2017).

9 S. S. Rao, *Vibration of continuous systems,* (John Wiley & Sons, 2007).

10 P. Gardonio and M. Brennan, Mobility and impedance methods in structural dynamics, in *Advanced Applications in Acoustics, Noise and Vibration* (CRC Press, 2004).

11 E. L. Hixson, *Shock and vibration handbook,* **10**, 1-46, (1988).

12 S. Sanei and H. Hassani, *Singular spectrum analysis of biomedical signals* (CRC Press, 2015).

13 S. M. Mohammadi, S. Enshaeifar, M. Ghavami, and S. Sanei, "Classification of awake, REM, and NREM from EEG via singular spectrum analysis," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 4769-4772 (2015).

14 A. Hossein Vahabie, M. M. R. Yousefi, B. N. Araabi, C. Lucas, and S. Barghinia, "Combination of singular spectrum analysis and autoregressive model for short term load forecasting," in *Power Tech, IEEE,* Lausanne, 1090-1093 (2007).

15 B. Kilundu, X. Chiementin, and P. Dehombreux, J Vib. Acous., **133**, 051007 (2011).

16 T. Liu, J. Chen, and G. Dong, J Vib Cont., 1506-1521 (2013).

17 B. Muruganatham, M. Sanjith, B. Krishnakumar, and S. Satya Murty, Mech. Sys. Sig. Proc., **35**, 150-166 (2013).

18 H. Al-Bugharbee and I. Trendafilova, JSV, **369**, 246-265 (2016).

19 H. Al-Bugharbee and I. Trendafilova, Int. J. Cond. Mont., **7**, 26-35 (2017).

20 D. Salgado and F. Alonso, J Mat. Proc. Tech., **171**, 451-458 (2006).

21 B. Kilundu, P. Dehombreux, and X. Chiementin, Mech. Sys. Sign. Proc., **25**, 400-415 (2011).

22 D. Garcia, I. Trendafilova, and H. Al-Bugharbee, "Vibration-based health monitoring approach for composite structures using multivariate statistical analysis," in *EWSHM-7th European workshop on structural health monitoring* (2014).

23 N. Golyandina and A. Zhigljavsky, *Singular Spectrum Analysis for time series.* (Springer Science & Business Media, 2013).

24 H. Hassani, "Singular spectrum analysis: methodology and comparison," (2007).

25 L. Zhang, J. Marron, H. Shen, and Z. Zhu, J Comp. Grap. Stat., **16**, 833-854 (2007).

26 H. R. Al-Bugharbee, *Data-driven methodologies for bearing vibration analysis and vibration based fault diagnosis*, (PhD thesis, University of Strathclyde, 2016).