Classification-based Damage Localization in Composite Plate using Strain Field Data

R Janeliukstis*, S Rucevskis and A Chate

Institute of Materials and Structures, Riga Technical University, Riga, Latvia

E-mail: Rims.Janeliukstis_1@rtu.lv

Abstract. Problem of damage localization in a cantilevered composite plate using strain data is tackled. The plate is partitioned into a number of zones and a mass equal to 9.43% of plate’s mass is put in each of these zones subsequently. The composite plate is harmonically excited via piezoelectric actuator with a series of driving frequencies equal to natural frequencies of the plate extracted in modal analysis test. In each of these events, the mechanical strains are recorded with strain gauges. Mean values of strain time series are calculated and used as a feature for building a classification model in which zones of the plate serve as classes. Linear discriminant classifier initially yielding the best classification accuracy (90.7%) is selected. The classification model is validated by selecting 5 query points on the plate and localizing the unknown query points in terms of classes (zones) of the plate. Overall, the unknown query points were classified successfully with only slight misclassification for the point at the boundary between 2 zones.

1. Introduction

The vast field of machine learning has applications in chemistry, medicine, biology, economics and sports among other. Relatively recently, engineers and scientists have discovered the virtues of using the methods and ideas of data science to tackle the challenges in civil, mechanical and aerospace engineering. One of the most prominent problems lies in the identification of damage — a subdomain of structural health monitoring. The underlying idea behind SHM is the installation of particular types of sensors on the structure of interest or embed them within the structure, if possible [1]. The signal of structural response modified by some disturbance may signalize the change of integrity of the structure [2]. It is of essential importance to fuse the sensor data and extract the damage sensitive features to successfully apply the machine learning algorithms in order to, for example, classify if the particular element of the structure is damaged or not and what is the severity of the damage and so on.

The advantages of composite materials over the more conventional ones (concrete, wood, metals, ceramics, etc.) are well known, hence it is crucial to ensure that composite structures maintain their integrity throughout their service life. The vast exploitation of composites in aerospace and their vulnerability to impact damage [3-6] has led researchers to develop damage identification methods based on machine learning approaches. In [7] authors simulated defects of various severities in different locations of a composite plate and used a mixture of support vector machines and decision trees to obtain the probabilities of the position of damage. In [8] researchers studied impacted composite plates equipped with piezoelectric sensor and actuator. The Wavelet Packet Transform was used to extract damage sensitive features and linear discriminant classifier was employed to classify damaged and healthy patterns of the plates. Researchers in [9] applied various $k$-nearest neighbour classifiers to classify different types of defects in aluminium and composite specimens, equipped with
piezoelectric patches for actuation and sensing. These authors also used machine learning to distinguish between influences of different temperatures in [10]. In [11] authors developed a numerical model for localization of added mass on a cantilevered composite plate equipped with strain sensors. The plate was partitioned into 18 zones and k-nearest neighbours, as well as decision trees classifiers were used to localize simulated query points to belong to one of these 18 zones.

In the present study, the location of added mass on a cantilevered composite plate is found by employing the classification approach of recorded strain signals. The plate is partitioned into 18 zones and in each of these zones a mass of 9.43 % of plate’s mass is placed and strains in the form of time series are recorded from 2 strain gauges (one mounted in parallel and the other in perpendicular direction to fibre orientation). The mean values of strains are extracted as a sensitive feature to mass position and used as an input for linear discriminant classifier. After training the classification model with 90.7 % accuracy, the model is validated on 5 query points of mass position on the plate. Results suggest a promising tool for localization of local changes in mass of the structure.

2. Damage localization based on linear discriminant classification

2.1 Linear discriminant classifier

Discriminant classification models assume that different classes \( y \) generate data \( x \) based on different Gaussian distributions. The space of \( x \) values divides into regions where a classification \( y \) is a particular value. For linear discriminant analysis the regions are separated by straight lines. The equation for such a boundary between two classes \( x_i \) and \( x_{i+1} \) is

\[
K + L(i) \cdot x_i + L(i + 1) \cdot x_{i+1} = 0
\]  

where \( K \) is the constant term obtained from a linear discriminant classifier model, \( L \) is the slope term for the two classes, also obtained from a classifier model.

Classification based on linear discriminant involves the following steps [12]:

- **Classifier training** – the fitting function estimates the parameters of a Gaussian distribution for each class:
  - the sample mean
  
  \[
  \hat{\mu} = \frac{\sum_{n=1}^{N} M_{nk} x_n}{\sum_{n=1}^{N} M_{nk}}
  \]  

  where \( M_{nk} \) is \( N \times K \) class membership matrix with the property

  \[
  M_{nk} = \begin{cases} 
  1 & \text{if observation } n \text{ is from class } k \\
  0 & \text{otherwise}
  \end{cases}
  \]  

  - the sample covariance is calculated by first subtracting the sample mean of each class from the observations of that class, and taking the empirical covariance matrix of the result

  \[
  \Sigma = \frac{\sum_{n=1}^{N} \sum_{k=1}^{K} M_{nk} (x_n - \hat{\mu}_k)(x_n - \hat{\mu}_k)^T}{N - K}
  \]  

  (the model has the same covariance matrix for each class, only the means vary).

- **Prediction of the new data** – the trained classifier finds the class with the smallest misclassification cost [13]

  \[
  \hat{y} = \arg\min_{y=1,...,K} \hat{P}(k|x)C(y|k)
  \]  

  where \( \hat{y} \) is the predicted classification, \( K \) is the number of classes, \( \hat{P}(k|x) \) is the posterior probability of class \( k \) for observation \( x \). Posterior probability is a product of prior probability (either with uniform or empirical distribution) and a likelihood function (which is usually of multivariate normal density). \( C(y|k) \) is the cost of classifying an observation as \( y \) when its true class is \( k \).
2.2 Damage localization based on linear discriminant classification

In this study, a non-destructive approach is applied to localize the local changes of mass on the composite plate. The plate is by no means damaged – a pseudo defect is introduced using a small weight of 20 g, comprising 9.43% of plate’s mass. The essential steps of damage localization are depicted in figure 1.

![Figure 1. Damage localization scheme based on strain feature classification.](image)

1. The plate is clamped at one end yielding a cantilever configuration. A piezoelectric actuator from MFC (macro-fiber composites) is mounted close to the clamping. This system is placed on rigid floor.

2. MFC element is used to excite the structural vibration in the plate and an experimental modal analysis is carried out with an aid of scanning laser vibrometer. Vibration velocity is measured and Fast Fourier Transform of the velocity is calculated to obtain the vibration spectrum. Natural frequencies (peak picking method) and mode shapes of the plate are extracted using POLYTEC software.

3. The plate is instrumented with 2 strain gauges – one in the longitudinal direction with respect to the fiber orientation and one in transversal. Wave generator, signal amplifier and dynamic strain measurement system Spider 8 are connected to the strain gauges and MFC element.

4. The plate is partitioned into 18 zones and a small weight of 20 g is consequently placed in each of these zones. During this act, the plate is harmonically excited through MFC element with an amplitude of 10 volts peak-to-peak and a driving frequency equal to that identified from modal analysis (step 2). Time series of mechanical strain from both strain gauges is recorded. A total of 3 such measurements are made by placing the mass at each of 18 zones.

5. The strain data is collected and a feature sensitive to the position of the added mass is extracted from this data. By process of trial and error, it is found that mean value over the entire time series

\[
\mu_{1}^{SG1,Z1} = \frac{1}{n} \sum_{i=1}^{n} x_{i,1}, \\
\mu_{2}^{SG1,Z1} = \frac{1}{n} \sum_{i=1}^{n} x_{i,2}, \\
\mu_{3}^{SG1,Z1} = \frac{1}{n} \sum_{i=1}^{n} x_{i,3} 
\]

(6)

gives the best results. In equation (6) indices 1, 2 and 3 are numbers of measurement sessions, Z1 indicates zone 1, n is the number of samples in the timeseries. These mean values are collected from all 18 zones and both strain gauges forming a \((18 \cdot 3) \times 2\) matrix with 2 columns of predictor values and 54 rows of class (zone) labels

\[
\begin{bmatrix}
\{1\} & \{\mu_{SG1,Z1}\} & \{\mu_{SG2,Z1}\} \\
\vdots & \vdots & \vdots \\
\{18\} & \{\mu_{SG1,Z18}\} & \{\mu_{SG2,Z18}\}
\end{bmatrix}
\]
where curvy brackets indicate vectors with 3 components due to 3 measurements per each zone. For example, \(\{1\} = \{1 1 1\}^T\) and \(\{\mu_{SGL1, Z1}\} = \{\mu_{SGL1, Z1}^1 \mu_{SGL1, Z1}^2 \mu_{SGL1, Z1}^3\}^T\).

6. Various classifiers from MATLAB Classifier Toolbox are tested on the matrix presented in step 5. It is found that the linear discriminant classifier gives the best class separation with an accuracy of 90.7%. Hence, this classifier is used to train a classification model. Confusion matrix is computed to check for the misclassified class labels and to analyse strengths and weaknesses of the model for each class separately.

7. The model is validated using 5 points of mass application in the process of classifier training. The points are picked such to belong not only to one particular zone but also to lie on the boundary between two or more zones.

3. Experimental procedure

3.1 Composite plate with sensors

The photo of the clamped composite plate with installed sensors is shown in figure 2 (a). The material is prepreg carbon fiber laminate consisting of 32 layers of lamina with layer thickness of 89 μm and density of \(\rho = 1560 \text{ kg/m}^3\). The layer stacking sequence is \((90\ 0)_{32}\). Two strain gauges are soldered on the surface as shown in figure 2 (b). Strain gauge #1 is the farthest from MFC, perpendicular to fiber orientation, while strain gauge #2, in the direction of fibres, is the closest of the two to MFC element. Thin copper tracks are glued on the surface of the plate in order to ensure the proper electrical conductivity for the system.

![Figure 2. Cantilevered composite plate: (a) photo; (b) positions of sensors with active dimensions.](image)

3.2 Experimental modal analysis

The procedure is carried out by employing a POLYTEC PSV-400-B scanning laser vibrometer system consisting of a PSV-I-400 LR optical scanning head, OFV-5000 controller, PSV-E-400 junction box, a Bruel & Kjaer type 2732 amplifier, and a computer system with a data acquisition board and PSV software. The first step of experimental modal analysis consists of setting an outer edges and a scanning grid for the measured object. This scanning grid represents the resolution of extracted mode shapes. The size of the scanning grid is taken as \(5 \times 15\) points. The plate is excited with a piezoelectric MFC (macro-fiber composite) element (model M2807-P1 smart material) glued on the surface of the plate. The excitation signal is periodic chirp with a bandwidth of 5-800 Hz and resolution of 0.25 Hz. POLYTEC system permits measuring either displacement due to vibration, vibration velocity or acceleration in the plane perpendicular to the surface of the measured object at each of the points of the scanning grid. The resonance frequencies and corresponding mode shapes are obtained by taking the magnitude of the fast Fourier transform of the vibration velocity signal.
3.3 Dynamic strain measurement

The dynamic strain measurement system shown in figure 3 (a) consists of a waveform generator (Agilent 3322A 20 MHz Function/Arbitrary Waveform Generator) which is connected to the MFC actuator for harmonic excitation of the plate, signal amplifier (LE 150/025 Piezomechanik GmbH signal amplifier (230 V AC, serial number: 10902/936), strain measurement acquisition box (Spider 8 600 Hz/ DC HBM with USB adapter USBHBM2903) which is connected to both strain gauges using two channels and the waveform generator. Spider 8 system is connected to a personal computer through a USB port. The recorded strain signals are visualized in Catman software. In the software, the required measurement channels are activated and sensor parameters are set in accordance with table 1. The sensors are initially zero-balanced to start measurements from zero strain. The time series of strain from both strain gauges are measured simultaneously with a duration of 2 seconds and sampling frequency of 2400 Hz giving 4800 samples plus 1 sample at time $t = 0$ s. A total of 3 measurements are recorded for each zone of the plate. The positions 5 selected query points for validation of classification model are shown in figure 3 (b). The event of application of actual mass on one of the zones is shown in figure 3 (c).

![Figure 3](image)

**Figure 3.** Preparation for dynamic strain measurement: (a) strain measurement equipment with (1) waveform generator, (2) signal amplifier, (3) strain acquisition system Spider 8; (b) partition of the plate into zones and application of 5 query point masses; (c) photo showing application of mass on the cantilevered composite plate.

| Sampling rate | Sensor type | Sensor amplifier | Transducer type | Measuring range | Gage factor | Filter frequency | Bridge factor |
|---------------|-------------|------------------|-----------------|-----------------|-------------|-----------------|--------------|
| 2400 Hz (0.42 ms) | SG 3 wire, 350 Ω | SR30 600 Hz (base) | Quarter bridge | 3mV/V (4000 με) | 1.99 | Bessel low pass | 300 Hz 1 |

4. Results and discussion

4.1 Natural frequencies

The measured spectrum of vibration velocity averaged over all scanning grid of the plate is shown in figure 4 (a). In the bandwidth of 800 Hz a total of 8 peaks are identified. Peak picking method is applied to extract the natural frequencies from the spectrum. Due to the limits imposed on the paper length, only the results for plate excitation using natural frequency of the fundamental bending mode (figure 4 (b)) are presented.
4.2 Strain features

The excitation signal with a driving frequency equal to the fundamental frequency of the cantilevered composite plate along with recorded strain timeseries for the 1st zone is shown in figure 5.

4.3 Classification model and localization of added mass

The linear discriminant classifier is employed for training the classification model based on mean values of strains in every zone. The errors of the model are as follows: cross-validation error \( = 0.0926 \) (describes mean error of cross-validated model when predicting is based on data not used in training [14]) and resubstitution loss \( = 0.0741 \) (describes fraction of misclassifications over all the set of instances on the training data from the predictors of classification model). The number of cross-validation folds is set to the standard value of 10 folds [15]. A scatterplot of mean strain values from classification matrix, grouped by class labels (zones) is shown in figure 6 (a). Vertical dashed lines represent the class separation boundary according to the equation (1). The position of black stars in the plot represent the positions of 5 query points in the strain gauge #1 vs strain gauge #2 mean value plane.

The results of classification quality can be inspected using a confusion matrix with a row and the column for each class. Each matrix element shows the number of test samples for which the actual class is the row and the predicted class is the column. Good results correspond to large numbers down the main diagonal and, ideally, zero off-diagonal elements [15]. According to confusion matrix in figure 6 (b), 2 out of 3 observations (67 %) were classified to belong to the 2nd zone, while they...
actually belong to the 1st zone. 1 out of 3 observations (33 %) classified as 1st zone, while it is in 2nd zone. 1 out of 3 observations (33 %) classified as 14th zone, while it is in 10th zone. 1 out of 3 observations (33 %) classified as 10th zone, while it is in 14th zone.

The predicted probabilities for all 5 query points to belong to zones 1 to 18 are given in table 2. The query point #1 is correctly classified to lie in zone #1. According to figure 3 (b), query point #2 lies in the intersection of zones #9, 10, 11 and 12. Hence, there is an equal chance for it to be classified in one of these zones. The classifier classifies this point to belong to zone #10 (over 56 % probability) or to zone #12 (over 39 % probability). For zones #9 and 11 the probabilities are negligible. Misclassification is made for query point #3 – it is incorrectly classified to lie in zone #7, while it is on the boundary between zones #6 and 8. However, the mean strains in zones #6, 7 and 8 are, probably, very close to each other, hence this slight misclassification. For query point #4, the classifier predicts around 72 % probability for it to lie in zone #2 which is correct. The other 28 % of probability are attributed to zone #1 which is, of course, not correct but it is neighbouring zone and the strains vary just slightly. The query point #5 is correctly classified to belong to zone #5.

![Figure 6](image_url)

*Figure 6. Linear discriminant classification results for the fundamental bending mode of the composite plate: (a) Scatterplot showing class separation; (b) confusion matrix.*

| Query Point | Zone 1 | Zone 2 | Zone 3 | Zone 4 | Zone 5 | Zone 6 | Zone 7 | Zone 8 | Zone 9 | Zone 10 | Zone 11 | Zone 12 | Zone 13 | Zone 14 | Zone 15 | Zone 16 | Zone 17 | Zone 18 |
|-------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| QP1         | 1 (0)  | 2 (0)  | 3 (0)  | 4 (0)  | 5 (0)  | 6 (0)  | 7 (0)  | 8 (0)  | 9 (0)  | 10 (0) | 11 (0) | 12 (0) | 13 (0) | 14 (0) | 15 (0) | 16 (0) | 17 (1) | 18 (0) |
| QP2         | 1 (0)  | 2 (0)  | 3 (0)  | 4 (0)  | 5 (0)  | 6 (0)  | 7 (0)  | 8 (0)  | 9 (0)  | 10 (0.564) | 11 (0) | 12 (0.391) | 13 (0) | 14 (0.045) | 15 (0) | 16 (0) | 17 (0) | 18 (0) |
| QP3         | 1 (0)  | 2 (0)  | 3 (0)  | 4 (0)  | 5 (0)  | 6 (0)  | 7 (1)  | 8 (0)  | 9 (0)  | 10 (0) | 11 (0) | 12 (0) | 13 (0) | 14 (0) | 15 (0) | 16 (0) | 17 (0) | 18 (0) |
| QP4         | 1 (0.281) | 2 (0.719) | 3 (0)  | 4 (0)  | 5 (0)  | 6 (0)  | 7 (0)  | 8 (0)  | 9 (0)  | 10 (0) | 11 (0) | 12 (0) | 13 (0) | 14 (0) | 15 (0) | 16 (0) | 17 (0) | 18 (0) |
| QP5         | 1 (0)  | 2 (0)  | 3 (0)  | 4 (0)  | 5 (0)  | 6 (0)  | 7 (1)  | 8 (0)  | 9 (0)  | 10 (0) | 11 (0) | 12 (0) | 13 (0) | 14 (0) | 15 (0) | 16 (0) | 17 (0) | 18 (0) |

**Conclusions**
The localization of a pseudo defect on a cantilevered composite plate using strain data is demonstrated. The motivation behind this is that non-destructive approach allows for variations in defect size and other defect parameters without actually affecting the integrity of the structure. This problem is posed as one of classification – find the position of an added mass in terms of belonging of this position to one of zones of the plate.

At first, an experimental modal analysis using a scanning laser vibrometer is conducted and natural frequencies of the plate are identified. Secondly, the mass equal to 9.43 % of that of plate’s mass is placed on each of plate’s zones, the plate is excited harmonically with the frequency equal to the
fundamental natural frequency of bending and strains measured by two strain gauges (one parallel to the orientation of fibres and other in the perpendicular direction) are recorded in the form of time series. The next step is to extract the position-sensitive strain features from the time series. In this case, simply the mean value over entire time series proved to be an efficient feature yielding classification accuracy of 90.7%. Finally, the trained classifier is validated by classifying 5 different query points of mass application.

The proposed localization methodology is simple and gives promising results as all of the query points are localized with acceptable accuracy. Further research would deal with exploring the sensitivity of the approach with decreasing the added mass.

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