Detection of Fastener Failure in a Thermal Protection System Panel

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Abstract— This paper presents development methods and application results for a structural health monitoring (SHM) system for assessing the condition of mechanical fasteners in a test article representing a realistic portion of a thermal protection system. The test article is a carbon-carbon panel bolted through 15 brackets to a backing structure. Mechanical states considered include all bolts fastened to a nominal torque value, or one of the 15 bolts loosened. Four transducers on the backing structure provide actuation and sensing signals. Spectral functions are computed from all single and pairwise signal combinations: (cross) power spectral densities, transfer functions, and coherence functions. Automated analysis of the spectral functions shows frequency intervals exist over which the function values are indicative of the mechanical state of the test article. These frequency intervals are used to provide features for the SHM classifier. Statistical pattern recognition methods select a subset of the features. The status of the test article is determined as "undamaged" or "bolt j is loose." The overall localization accuracy of the SHM system on test data is 99.1% with 99.7% probability of detecting a damaged condition at a 0.2% probability of a false alarm.

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1. Introduction

Structural health monitoring (SHM) refers to automated methods for determining adverse changes in the integrity of mechanical systems [1]. The Air Force Research Laboratory's Air Vehicles Directorate at Wright-Patterson Air Force Base conducts research to sustain current airframe structures and intends to implement integrated health monitoring systems on future space vehicles. One focus area is a reusable launch vehicle known as the Space Operations Vehicle (SOV) [2]. The SOV is a key element of the future launch capability. This paper presents SHM laboratory experiments with a canonical element of a conceptual space operations vehicle.

Overview of Related Work

This work is an extension of the research presented in [3], where initial capabilities for damage detection and localization were established for the test article. This work is also similar to the excellent work presented in the series of articles by Worden, Manson, and Allman [4,5,6]. The authors methodically establish functions, features, and methods useful for novelty detection beginning with simple structures in the laboratory and an aircraft panel,

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and ending with localizing which one of a set of nine panels had been removed from an aircraft wing. In general, Worden et al found that selected spectral bands from transmissibility functions provide useful information for determining structural status. However, the search for determining useful frequency bands was accomplished with an exhaustive visual search of the transmissibility functions. The squared Mahalanobis distance is the preferred test statistic to determine novelty (i.e. damage). In [6], damage localization is accomplished with a multi-layer perceptron artificial neural network. This paper presents a damage localization system using three spectral functions, automated search methods for determining spectral bands and final feature selection, and a statistical classification method.

SHM and the Space Operations Vehicle

Carbon-carbon panels cover the fuselage of the SOV as part of a thermal protection system. If a panel was to lose one or more fastening bolts, the vehicle's fuselage could be exposed to the environment, compromising vehicle integrity, ultimately jeopardizing mission safety and effectiveness. Furthermore, the thermal protection system of the SOV is one of its most vulnerable components, due to the likelihood of space debris strikes and the certainty of extreme temperatures during re-entry. The thermal protection system must be in good condition before launch due to its critical role in protecting the vehicle's primary structures and subsystems. A desired operational feature of the SOV is a turn around time on the order of hours rather than months as required by space shuttles. SHM methods could significantly reduce turn around time by automatically assessing structural integrity of the SOV [7]. Therefore, automated SHM methods are needed to support the operational goal.

Statistical Pattern Recognition

We apply a statistical pattern recognition methodology for the SHM systems designed in this paper. The design process begins by collecting data from the structure. Vibration signals are applied to the structure and responses recorded for the damage conditions of interest. The signals are stored with corresponding structural state information. Then, a set of measurements, or feature vectors, are computed from the responses and associated with the structural state. The resultant information provides labeled data for classifier design. Statistical classifier design involves the specification of discriminant functions estimated from the statistics of the feature vectors. Finally, performance of the designed classifier is estimated by applying labeled feature vectors to the input and measuring the resultant classification accuracy.

2. Experiments

The Canonical Element

All experiments are conducted in the laboratory with a single carbon-carbon panel. We consider the canonical element to be the simplest collection of elements approximating a space operation vehicle's thermal protection system, as depicted in Figure 1. A carbon-carbon panel provides the foundation of the thermal protection system. The panel is approximately 2' x 2' x 1/8" and is bolted to 15 evenly spaced brackets with $\frac{1}{4} \times 20$ bolts. The brackets are in turn bolted to a 0.1" thick ribbed backing structure with 0.67" ribs. The backing structure represents the vehicle's fuselage. Figure 2 is a side view of the canonical element showing the connection details of the carbon-carbon panel, brackets, and backing structure. Four piezoelectric transducers are fastened in the valleys between the ribs of the backing structure. The transducers are attached on the side of the backing structure representing the inner fuselage of the aerospace vehicle where temperatures should remain well within the operating range of the piezoelectric materials.

This configuration represents realistic sensor placement since piezoelectric devices will fail at the high temperatures encountered on the outer surface of an SOV. Also, the complex mechanical structure of the canonical element hints at the level of difficulty inherent in field applications.

Figure 3 shows a diagram of the canonical element including sensor placement and bolt numbering for the experiments described in this paper. In all experiments, sensor 1 provides the activation signal and responses are recorded at sensors 2, 3, and 4.

Structural Conditions

Different structural conditions are obtained by loosening one bolt at a time from the carbon-carbon panel by a one-quarter turn counterclockwise. The particular arrangement of loose and tight bolts is referred to as a bolt pattern and bolt pattern j represents the condition of bolt j loose; bolt pattern 0 represents the baseline, or healthy, condition of all bolts fully fastened. A bolt loose condition corresponds to a damaged state. We define two types of structural health monitoring tasks, damage detection and damage localization. The damage detection task requires identification of only two states: healthy or damaged. Damage localization refers to identifying which bolt, if any, is loose from the TPS panel. The localization experiment requires identification of one of 16 possible bolt patterns. The system must declare the structure healthy or specify which bolt is missing.

Signal Generation and Collection Equipment

Signals are generated and recorded using Labview version 6.1 software, with a National Instruments PXI 6120 data acquisition card. A Fluke PM5193 Programmable Synthesizer/Function Generator produces a swept frequency sinusoid, 0 to 7000 Hz in approximately 1 second as the broadband excitation signal.

The stimulus is amplified to approximately 60 volts peak to peak with a Krohn-Hite 7500 then applied to piezoelectric disk transducers of approximately $\frac{1}{4}$" diameter. Responses are collected for 30000 samples at a 20 kHz sample rate and 16-bit analog to digital conversion.

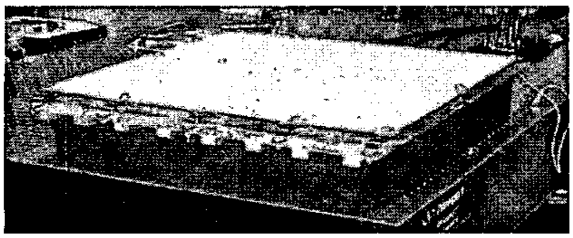

Figure 1. Top view of the canonical element showing carbon-carbon TPS panel, surface bolts and washers. The brackets visible at the top and bottom edges connect the panel to the backing structure.

Data Collection Procedure

Vibration data from healthy and damage states corresponding to different bolt patterns are collected in rounds as follows:

- all bolts are tightened to 20 in-lbs;
- N stimuli are applied to piezoelectric transducer 1;
- the stimulus and N responses are recorded from piezoelectric transducers 2, 3, and 4;
- bolt j is loosened;
- the stimulus and N responses are recorded from piezoelectric transducers 2, 3, and 4;
- bolt j is tightened.

These steps are repeated for bolts $j = 1 \ldots 15$. In different rounds, N varied from 3 to 25, providing 45 to 375 responses from the healthy condition and an equal number of responses from the damaged conditions. The fully fastened condition corresponds to 20 in-lbs of torque, the maximum rated value for the carbon-carbon panel. A pass through $j = 1 \ldots 15$ constitutes one round of data. The data were collected from 43 rounds collected during a 7-week interval.

Feature Design

To develop a classification system with the ability to correctly classify all sixteen damage conditions (all bolts tight and 15 conditions where one bolt is loose) features must be designed that have the ability to discriminate between damage conditions. The basis for the features is the output of the MATLAB® 'spectrum' function [8]. The eighteen output functions of interest are:

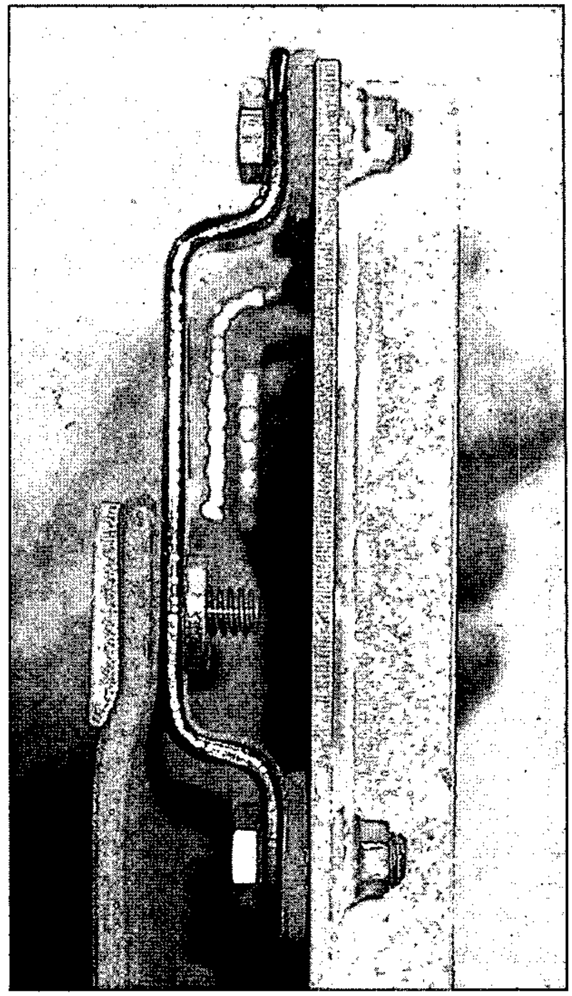

Figure 2. Side view of the canonical element showing fastening details of the TPS panel to the backing structure with bolts and brackets. The piezoelectric transducers are attached to the right hand side of the backing structure.

- power spectral density at each of the 3 sensors (3 output functions)
- cross power spectral density for each potential pairing of the 3 sensors (3 output functions)
- transfer function from the input signal to each of the 3 sensors (3 output functions)
- modified transfer function (not using input signal) between each pairing of the 3 sensors (3 output functions)
- coherence function from the input signal to each of the 3 sensors (3 output functions)
- coherence function between each pairing of the 3 sensors (3 output functions)

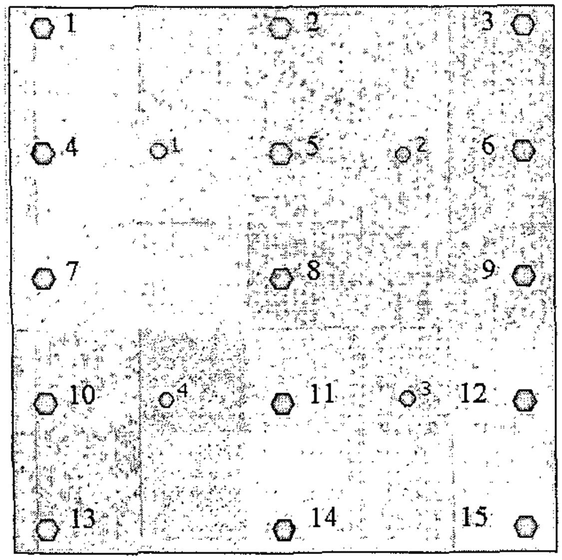

Figure 3. Diagram of bolt and sensor placement for the experiments described in this paper. Although the piezoelectric transducers are visible in this drawing, they are attached to the far side of the backing structure.

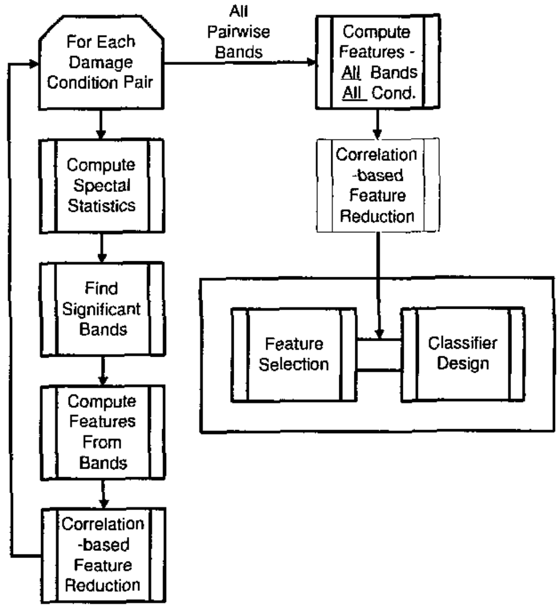

Figure 4. Overview of the methods for candidate feature generation and reduction. The final set of candidate features are input to a feature selection process.

Given 18 output functions, a 4096-point FFT (2049 resulting frequency bins), and 16 damage conditions, the search for meaningful features can be very time consuming. To make a thorough search for features practical, the automated process presented in Figure 4 was implemented.

To make the automated process tractable, instead of searching for individual frequency bins in each of the 18 output functions of interest that have some ability to discriminate between all 16 damage classes, the problem is broken down into a series of two class problems. Given 16 structural conditions, there are 120 potential pairs of classes. Therefore, we endeavor to find features that are able to discriminate between two of the 16 classes at any one time. Further simplification comes from considering groups of contiguous frequency bins (bands) from each of the 18 output functions in turn. We define a 'band' as containing:

- begin frequency (the lowest frequency value of a group of contiguous frequency bins)
- end frequency (the highest frequency of the group)
- output function (which function the band is from)
- operation (either 'sum,' 'max,' or 'min') to perform on the bin values in the band to create a single feature value

Compute Spectral Statistics

Considering each of the 120 two class problems (damage condition pairs) in turn, we compute an average output function (i.e. transfer function at sensor 2) with a confidence interval for each of the 18 output functions of interest as follows:

1. Choose a representative assembly of rounds of collected response data, M (only 10 rounds are used to compute the spectral statistics).
2. Compute all 18 output functions of interest for each observation relating to the first damage condition of the current pair of damage conditions (1 pair out of 120).
3. For each bin, compute the mean bin value and standard deviation across all bins on all output functions for this particular damage condition.
4. Repeat Steps 2 and 3 for the second damage condition of the current pair.

After this process, we have a mean function and a standard deviation function that can represent the expected value and confidence interval bounds for each bin and every possible combination of two structural conditions to be separated.

Find Significant Bands

In this step, we search for bands of contiguous frequency bins where there is at least as much separation between the confidence intervals of the two damage conditions in the current pair as the total width of the two confidence intervals for that frequency bin. Groups of some minimum number of contiguous frequency bins meeting these criteria are recorded as bands (begin and end frequencies for the particular output function). A further check is performed to ensure that the band comes from a portion of the output function that is significant (i.e. exceeds a threshold for the mean value).

Bands are identified for each of the 18 output functions of interest. A final step is to create 3 potential features from each initial band by applying an operation across the frequency band to create a scalar feature. The three operations are 'sum,' 'min,' and 'max.'

Compute Features From Bands

Now that we have identified bands wherein there should be statistically significant separation in values between the two damage conditions being considered, we go back through the M = 43 rounds of data and compute features for each observation relating to any one of the two damage conditions being considered. This process creates a feature matrix and a corresponding class label vector.

Correlation-based Feature Reduction

Now that we have a multitude of features that may separate the two classes currently being considered, we need to reduce the total number of features by keeping only those features that are relatively uncorrelated to each other but highly correlated to the damage condition. This is accomplished by augmenting the feature matrix by adding the class label vector as the first column in the matrix, in effect making the first 'feature' for each observation be its class label. Next, we compute a correlation coefficients matrix. The absolute value of the elements in this matrix are used in the following way to reduce the number of features:

1. Keep only those features with correlation coefficients relating to the class label above a threshold.
2. Identify groups of features with cross-correlations above a threshold.
3. For each group identified in Step 2, retain only the feature with the highest correlation to class label.

Now we have a set of relatively uncorrelated features that may be expected to have some discrimination ability between the two classes currently being considered.

Compute Features From All Bands, For All Damage Conditions

Once all bands have been designed for each of the 120 damage condition pairs, all of the remaining bands are used to compute features on all observations (regardless of damage condition) for each of the M = 43 rounds of data being used to design features.

The same correlation-based feature reduction procedure is performed, except that observations of all 16 classes are considered at the same time. During this step, features that survive must have some level of correlation to the class label for all damage conditions.

Classifier Design

Classification is accomplished using one discriminant function for each structural state to be recognized. The discriminant functions are derived from the multivariate Gaussian class-conditional probability density functions as: [9]

$$d_j(x) = -(x-\mu_j)^t\Sigma^{-1}(x-\mu_j) - \log|\Sigma_j| \qquad (1)$$

where x is a feature vector to be classified, $j = 0\ldots15$, representing the healthy condition and 15 unique damage conditions, and μ_j and Σ_j are the mean and covariance matrices of all feature vectors corresponding to the $\jmath^{\text{th}}$ structural state.

Elements of the feature vector are determined in the feature selection process. Classification is accomplished by evaluating each discriminant function for the input x, then assigning the category according to the discriminant function with the largest value. Damage detection outcomes may be obtained by treating categories $j = 1\ldots15$ as the damage state and $j = 0$ as the healthy state.

Feature Selection

Feature selection provides a subset of measurements from the feature pool most useful for classification. In general, the fewer features used in a classifier, the more likely the training set performance will be representative of test set performance.

We use a sequential floating forward selection method as described in [10]. A brief description is given here. The current optimal feature set is initialized to the empty set. Then the "best" feature is added to the optimal set by determining which feature provides the greatest quality metric, usually related to classification accuracy. The current feature set and corresponding quality metric are stored for comparison in a subsequent step. In the next step, the "worst" feature is determined. The worst feature is defined as that feature, which when removed from the current feature set, provides the greatest quality metric. The feature set and quality metric from this step are also stored. The quality metrics of the candidate feature sets obtained from adding the best and removing the worst features are compared. The chosen feature set is selected to provide the largest quality metric. The process repeats until a stopping criterion is achieved, typically an upper limit on the number of features, or until the quality metric stops increasing.

A key element of feature selection is the quality metric. Since the final system must perform well on data not available during training, we use a hold out method in computing the quality metric to preferentially select features that generalize to independent test data.

Recall, $M = 43$ rounds of training data are obtained by recording responses through the set of 16 possible zero and one bolt at a time loose structural states. We hold out one round of the data, perform feature selection on the remaining (M-1) = 42 rounds of data, apply a classifier using the candidate feature set to the held out round, and record the average localization accuracy for that round. We repeat these steps a total of M = 43 times, so each round is held out then tested to provide a hold out localization accuracy. The quality metric for a candidate feature set is the average hold out localization accuracy.

3. Analytical Efforts

We believe that exploiting information about the physical structure is essential for long term success of any SHM system. Therefore, in addition to the signal processing and pattern recognition approach, analytical techniques for assessing the dynamic response of the test article are applied.

Analytical techniques, such as the finite element method, can be used to predict the changes likely to result from particular types of damage, as well as to facilitate sensor placement and assess damage severity. A finite element model of the stiffened carbon-carbon TPS panel with the backing structure has been generated as shown in Figure 5. In this simple model the bolts are not explicitly modeled, but boundary conditions are imposed at each bolt location to reflect either a fixed or free condition corresponding to an undamaged or completely failed bolt.

To assess the vibrational characteristics and mode shapes of the pristine structure as well as that of the damaged configurations, a series of natural frequency analyses have been performed. Fundamental frequencies and mode shapes for the undamaged structure and for the structure with a missing bolt are shown in Figures 6 and 7. Comparing these figures indicates that at some modal frequencies the bolt loss has little impact on dynamic response, while in other cases there is a significant change in both mode shape and frequency. Such results are useful in selecting classifier features suitable for detecting the damage conditions of interest. The analyses also indicate that the loss of a bolt has a relatively local effect, which has significant implications to actuator/sensor placement. Utilizing a series of analyses of various damage configurations, it is possible to determine if a particular actuator/sensor pattern will detect all the possible bolt failures.

The complete failure of a bolt allows new frequencies and mode shapes to occur which provide clear signals for indication of bolt damage. Obviously, a primary goal of any SHM system would be to detect damage prior to the loss of an entire bolt. To better understand the effects of partial damage in bolted connections, analysis techniques are being developed to incorporate the influence of bolt damage on the resulting dynamic behavior of the structure assuming that the bolt damage can be simulated analytically and experimentally as a loss of preload in the fastener. Detailed models incorporating changes in local stiffness due to loss of preload are underway.

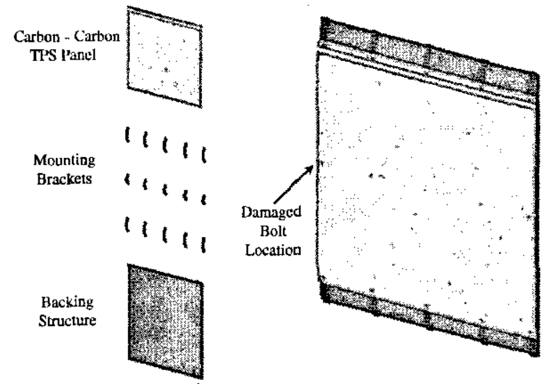

Figure 5. TPS assembly finite element model. Modeled components include the carbon-carbon panel, mounting brackets and backing structure.

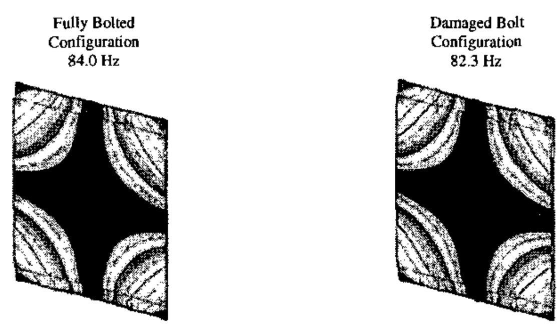

Figure 6. Finite element analysis showing damage *insensitive* vibrational mode shapes.

4. Results

Feature Selection

The feature selection process returned the 12 element feature set shown in Table 1. The 'Function' column indicates which spectral function and sensor(s) provide the raw input signal. The letter 'P' indicates a (cross) power spectral density, and 'T' indicates a transfer function while the subscripts show the sensor indices. The 'Operation' column denotes the operation applied to the spectral function values, and the 'Interval' column shows the frequency range used for that feature.

Classification Accuracy

Results from the classification experiments are shown in the confusion matrix of Table 2. These test results are accumulated across the held out rounds from the fea-

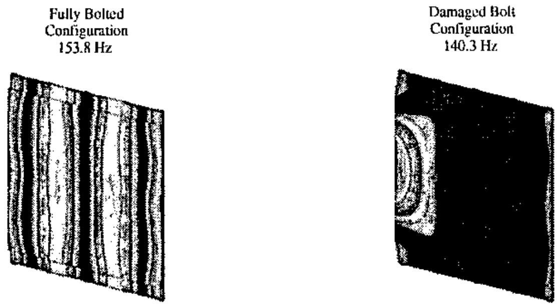

Figure 7. Finite element analysis showing damage *sensitive* vibrational mode shapes.

ture selection process. That is, these results are from 43 different classifiers, all using the same feature set, but trained with a unique collection of 42 rounds of data. The average accuracy across all the tests is 99.1%. The lowest accuracy for a given round is 96%. The probability of false alarm (declaring a loose bolt given a healthy system) is $(11/4658) = 0.2\%$ and the probability of a missed detection (declaring a system healthy given a loose bolt) is $(9/3525) = 0.3\%$. Therefore, the probability of correctly declaring damage for any loose bolt condition is 99.7%.

5. Conclusions

This paper provides an improved version of a structural health monitoring system for a difficult structural health monitoring task, relative to [3]. A primary factor leading to the improvement is the automated feature generation approach. In this step, frequency intervals that reliably separate pairs of structural conditions are first identified. Then, candidate features are computed from those frequency intervals and re-evaluated to measure how well they may be expected to separate all the structural conditions under consideration. Final features are obtained by a hold out based feature selection method. The resultant system has substantially higher localization accuracy than presented in [3], as well as a higher probability of detecting damage and lower probability of false alarm. The automated methods developed in this work should be applicable to a variety of structures. One of the most important elements in this approach is to provide relevant training data. In this study, a single carbon-carbon panel is tested in a laboratory environment. Therefore, vibration and acoustic loads from other areas of the vehicle are not considered in these experiments. We are currently working to apply these methods to different SHM tasks and to better exploit information obtained from analytical methods.

Table 1. Details of selected features.

Index	$\text{Function}_{i,j}$	Operation	Interval (Hz)
1	P_{34}	Sum	4570 - 4590
2	P_{44}	Max	4819 - 4932
3	P_{14}	Sum	5283 - 5376
4	P_{33}	Sum	5195 - 5347
5	P_{44}	Max	5050 - 5127
6	T_{12}	Sum	5820 - 5972
7	P_{44}	Sum	4570 - 4590
8	P_{34}	Sum	3887 - 3970
9	P_{34}	Sum	3716 - 3735
10	T_{34}	Sum	3916 - 3945
11	P_{33}	Sum	3901 - 3936
12	P_{44}	Sum	3887 - 3901

Table 2. Confusion matrix for the damage localization experiment. This confusion matrix shows the number of occurrences of each classification outcome for each actual damage location. The row and column indices of the confusion matrix correspond to the number of the bolt that is actually loose and the bolt number assigned by the classification decision. Bolt '0' corresponds to the all bolts fully fastened condition.

	Assigned															
Actual	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	4647	0	1	1	0	0	0	0	9	0	0	0	0	0	0	0
1	0	233	0	2	0	0	0	0	0	0	0	0	0	0	0	0
2	2	1	232	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	235	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	215	0	0	0	0	0	20	0	0	0	0	0
6	0	0	0	0	0	0	233	0	0	1	1	0	0	0	0	0
7	0	0	0	5	0	0	0	230	0	0	0	0	0	0	0	0
8	7	0	0	0	0	0	0	0	228	0	0	0	0	0	0	0
9	0	0	0	0	1	0	0	5	0	226	0	0	0	0	0	3
10	0	0	0	0	5	0	0	0	0	1	229	0	0	0	0	0
11	0	0	0	0	0	0	0	1	0	0	0	233	1	0	0	0
12	0	0	0	0	0	0	0	0	0	1	5	0	229	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	235	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	235	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	235

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