APPLICATION OF UNSUPERVISED SUPPORT VECTOR MACHINE FOR CONDITION ASSESSMENT OF CONCRETE STRUCTURES

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ABSTRACT

This paper presents research work that aims at developing a robust method for condition assessment of real-life concrete structures for the detection of small cracks at an early stage of development. A method is presented that utilises an unsupervised one-class support vector machine (SVM).Measured acceleration data from the current state of a structure are used as input parameter. The first singular value of the measured response data is utilized for training and testing of new data sets. Two damage identification approaches are demonstrated, one implementing the SVM for each measurement sensor separately, and another one implementing the SVM for all sensors combined. The use of one-class SVM is well suited for the condition assessment in structural health monitoring since they can detect the advancement of cracks by assigning progressively negative decision values. The presented method is based on unsupervised and non-model-based approaches, and hence there is no need for any representative numerical/finite element model of the structure to be created. To demonstrate the feasibility of the method in the detection and assessment of gradually evolving deterioration, it is tested on a replicate structure of a concrete jack arch which is a main structural component on the Sydney Harbor Bridge – one of Australia's iconic structures. The test structure is a concrete cantilever beam with an arch section which is located on the eastern side of the bridge underneath the bus lane. A cut is introduced to the structure using a saw and its length is progressively increased in four stages while the depth is kept constant; these four damage cases correspond to less than 0.5% reduction in the first three vibrational modes of the structure which is considered a very small damage. It is demonstrated that the presented method can reliably detect the progression of the crack in the structure and thus can enable the real-time monitoring of infrastructures.

KEYWORDS

Structural Health Monitoring, One-Class Support Vector Machine, Singular Value Decomposition, Damage Detection, Acceleration, Concrete Structure, Condition Assessment, Sydney Harbour Bridge.

INTRODUCTION

All civil structures have finite lives, and they begin to deteriorate as soon as they are put into service, due to processes such as corrosion, fatigue, erosion, wear and overloading. To ensure the safety and reliability of ageing infrastructures, the concept of structural health monitoring (SHM) was developed in the 1960s and is applied today by infrastructure owners and authorities to assess the health condition of a structure. SHM enables early and reliable damage detection and health assessment, and thereby prevents catastrophic failures and allows the extension of a structure's lifespan. In general, SHM covers continuous, global and automated monitoring practices that aim at detecting, locating and estimating any introduced damaged or any growth of inherent faults in a structure and enables the decision making on actions of safety measures and the predication on a structure's residual life, following Rytter's hierarchy (Rytter, 1993).

The fundamental questions for the design of a SHM system are, as stated in (Cross et al. 2013); what can be measured that correlates to damage, how to measure it, and, importantly, how to use the raw measurements to make inferences and decisions about structural condition. To date, the most common measurements for SHM systems are the vibration responses of a structure (Makki Alamdari et al. 2014). These global measurements contain information about the mass, stiffness and damping of a structure and can thereby reflect structural changes due to damage. Measurements of acceleration along with strain are the most commonly used quantities

in SHM systems, but also other measurements such as acoustic emissions, electrical impedance are being employed. An ideal SHM system comprises of a large number of heterogeneous sensors installed across the structure at various locations.
After the collection of raw measurements, a SHM system faces two challenges, one is feature extraction and the other is pattern recognition. Since damage fingerprints are typically deeply embedded in the raw measurements, a parameter must be formulated that extracts the damage features from the measured raw data. This feature extraction process usually also involves dimensional reduction. Some traditional damage sensitive parameters are resonant frequencies, mode shapes, modal flexibilities, modal stiffness and modal strain energy. Feature extraction methods include modal analysis and statistical methods such as principal component analysis or singular value decomposition.

Once a particular feature has been extracted, it must be classified using pattern recognition techniques to determine whether it has arisen from the damaged or undamaged structure, and at higher levels of SHM, classified as to the location, type and severity of the damage if present (Cross et al., 2013). Pattern recognition techniques include supervised learning approaches such as neural networks, support vector machines and Gaussian processes (Worden et al., 2011) and novelty detection such as outlier analysis and the use of statistical process control charts(Worden et al., 2004). While supervised learning approaches require data from damaged states of a structure, novelty detection methods only rely on data from the undamaged condition of a structure, which is most often the case for practical applications of in-situ structures.

This paper presents a damage identification method that is applicable to SHM systems of in-situ structures where only data of the current (undamaged) state is available. The method uses acceleration response measurements as raw data and applies single value decomposition (SVD) as feature extraction technique and one-class support vector machine for pattern recognition. The method is validated on experimental data from a laboratory test structure that represents a replica of a concrete jack arch from the Sydney Harbor Bridge. Progressive damage of four stages is inflicted to the test structure and the vibrational responses are captured by a number of accelerometers at the healthy and each damaged state. Two damage identification approaches using the presented method are demonstrated, one approach implements the SVM for each measurement sensor separately, and the other approach implements it for all sensors combined. The results show that both approaches are robust in detecting the presence of damage. The second approach is also successful in reliably indicating the progression of damage.

BACKGROUND

Support Vector Machine

Support Vector Machine (SVM) (Cortes & Vapnik, 1995) is a supervised learning technique with strong theoretical foundations based on the Vapnik-Chervonenkis theory. It has a strong regularization property, which is the ability to generalize a model to new data. These characteristics help to overcome overfitting, which is a common issue for neural networks. Furthermore, SVM can unify different types of discriminant functions such as linear, polynomial, radial basic functions in the same framework.

In the context of this paper, **x**is a feature vector extracted from sensor data, $y \in \{-1,1\}$ the label of **x**, where y = −1 means that **x** is recorded from a damaged bridge component and y = +1 means that **x** is measured from a healthy component. We want to find a hyperplane with maximum margin that separates the points with labels y = +1 from those having y = −1.

The classification model is a function, $f: R^d \rightarrow \{-1,1\}$. It is in the form: $f(x) = \mathrm{sgn}(w \cdot x - b)$ where '.' is the dot product, sgn(x) = +1 if x > 0 and sgn(x) = −1 otherwise. **w** and b are the parameters of the model and can be learned from training data. Given a set of *n* training samples, $\{(x_i, y_i)\}_{i=1}^{n}$, the training process determines the model parameters **w** and b by minimizing the classification error on the training set while still maximizing the margin. Mathematically, it is equivalent to the following minimization problem:

$$\min_{w,\xi,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \xi_i \tag{1}$$

$$\text{such that} \qquad y_i(w \cdot x_i - b) \geq 1 - \xi_i, \;\; \xi_i \geq 0, \;\; i = 1, \cdots, n, \tag{2}$$

where ξ_i is a slack variable for controlling how much training error is allowed and C is the variable for controlling the balance between ξ_i (the training error) and **w** (the margin). The problem can be transformed to the dual form using Lagrangian multiplier:

$$\max_{\alpha_1,\cdots,\alpha_n} \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i\alpha_j y_i y_j x_i.x_j \quad (3)$$

such that $\sum_i \alpha_i y_i = 0, \;\; 0 \le \alpha_i \le C, \;\; i = 1, \cdots, n. \quad (4)$

This problem can be solved using quadratic programming. The learned classification model $f(x) = sgn(w \cdot x - b) = sgn(\sum_i \alpha_i y_i x_i x - b)$ will be used to determine if a new data instance is coming from a healthy or damaged bridge component. A health score for a new data instance, denoted as $\mathbf{x_{new}}$, can be generated as $\sum_i \alpha_i y_i x_i x_{new} - b$.

One-class Support Vector Machine

Due to the limited availability of damaged data for supervised learning, unsupervised or one-class approach is more practical. In this work, we use one-class SVM (Schölkopf et al. 2001), (Schölkopf et al., 1999) for damage detection. The algorithm is to find a small region containing most of healthy data points. They do that by mapping data into a feature space using a kernel function and then separating them from the origin with maximum margin. The Kernel function is a function that corresponds to an inner product in the feature space. This makes the algorithm to fit the hyperplane in a transformed high-dimensional feature space although we cannot linearly separate the two classes in the original feature space. Using the settings of supervised SVM learning with the origin as a second class, the one-class learning process can be formed as the following optimization problem:

$$\min_{w,\xi,b} \frac{1}{2}\|w\|^2 + \frac{1}{vn}\sum_{i=1}^{n} \xi_i - \rho \quad (5)$$

such that $\mathbf{w} \cdot \mathbf{x_i} \ge \rho - \xi_i, \;\; \xi_i \ge 0, \;\; i = 1, \cdots, n, \quad (6)$

where v has similar function as C in supervised SVM and n represents the number of training examples.

It is worth noting that the training dataset $\{x_i\}_{i=1}^{n}$ in this case only contains feature vectors and no label information is provided. Once the model is obtained, health score can be created in the same way as the supervised learning as $f(x) = sgn(\sum_i \alpha_i x_i x - \rho)$. A negative health score from a new data instance will indicate it is an anomaly, which is likely damage.

Feature Extraction

The method used in this paper is based on the Frequency Domain Decomposition (FDD) technique, which uses Singular Value Decomposition (SVD) of the spectral matrix. This section aims to provide a theoretical background of FDD.

Suppose a system under white Gaussian excitation. The relation between an unknown input and the measured response can be expressed by:

$$G_{xx}(\omega) = H(\omega)G_{ff}(\omega)H^T(\omega) \quad (7)$$

where G_{xx} is a $m \times m$ Power Spectral Density (PSD) matrix of the responses and G_{ff} is a $n \times n$ PSD matrix of the input excitation. H is a $m \times n$ Frequency Response Function (FRF) matrix. Under assumption of a white Gaussian input and lightly damped system, it can be proved that the PSD of response corresponds to Eigen-parameters of the system [(Brincker et al., 2000)].

In FDD, the first step is to estimate the PSD matrix of the response. At each frequency, the PSD matrix is decomposed by taking the SVD of the matrix as:

$$G_{xx}(\omega) = U\Sigma U^H \quad (8)$$

Where U and Σ are $m \times m$ unitary matrix of singular vectors and diagonal matrix of singular values, respectively. In this study, the first singular value of Σ at each frequency coordinate is utilized as damage sensitive feature and training of the model is performed according to the estimated first singular values of the measured responses at the healthy state of the structure.

EXPERIMENTAL CASE STUDY

The experimental set-up for this study is a reinforced concrete jack arch, which is one of the major structural components of the Sydney Harbor Bridge. There are 800 concrete jack arches on the underside of the deck of the bus lane, see Figure.1(a). For the bridge management, it is critical to detect any structural deterioration in the arches as early as possible in order to schedule the required inspection and repair. A steel reinforced concrete beam was manufactured with a similar geometry to those on the Sydney Harbor Bridge, see Figure.1(b). The length of the specimen was 2000 mm, the width was 1000 mm and the depth was 374 mm, see Figure.2(a) and (b).

A 16-channel NI PCI-6133 data acquisition was used to capture the force and resultant acceleration time histories. To measure the structure's vibrational response, the structure was excited using an impact hammer with steel tip, which was applied on the top surface of the specimen just above the sensor A9, see Figure.2 (a). The acceleration response of the structure was collected by 10 uniaxial PCB 352C34 accelerometers placed at the front face of the jack arch termed A1, A2, …, A10, see Figure.2(a). Measurement were recorded for 2 seconds at a sampling rate of 8 kHz, resulting in 16000 samples for each event.

After testing the benchmark structure in its healthy condition, a crack was gradually introduced to the specimen between sensors A2 and A3 with four levels of crack dimensions: (75 × 50) mm, (150 × 50) mm, (225 × 50) mm and (270 × 50) mm, see Figure.2 (c), (d), (e) and (f). A total of 190 impact test responses were collected from the healthy condition and at each level of damage severity.

In order to investigate the impact of damage on the natural frequencies, at each damage case, a comparison was made on the measured frequency responses. Figure.3 compares the Fast Fourier Transform (FFT) of four damage cases and the healthy state. As expected, the discrepancy is more obvious at higher frequencies, higher than 500 Hz, in this case, and there is not much distinguishable difference in frequencies lower than 500 Hz. It was realized that the change in the first three natural frequencies between the healthy state and all damage cases was less than 0.5% which corresponds to very small damage.

(a) (b)

Figure 1. Illustration of (a) the bus lane on the Sydney Harbour Bridge, (b) one of the concrete jack arches underneath the bus lane.

DAMAGE IDENTIFICATION RESULTS

First Approach: Implementation of SVM for Each Sensor Location

Two different approaches were implemented to build and train a model utilizing one-class support vector machine. In the first approach, for each sensor location and for all events, 190×5 (190 events for each state of the structure including one healthy state and four damage states), the features in the frequency domain were created as follows. For every vibration event, the data from each accelerometer were standardized to have zero mean and one standard deviation. Then the data were converted to the frequency domain to generate the power spectral density. Only half of the samples (8000) were used since the frequency spectra were mirrored with respect to the Nyquist frequency; hence, there were 8000 feature elements for each event. All 190 events from the healthy state of the structure were implemented to train the model. A separate model was constructed for each sensor location. The remaining data from four damage cases were implemented for the testing and an accuracy of 99% was effectively obtained for all sensor locations showing that all damage cases were correctly identified as a separate class. Then testing was separately performed for each damage case. All 190 events from each damage case were utilized for testing to detect the progress of damage in the structure. The results of the testing for all 10 sensors locations and four damage states are depicted in Figure 4.

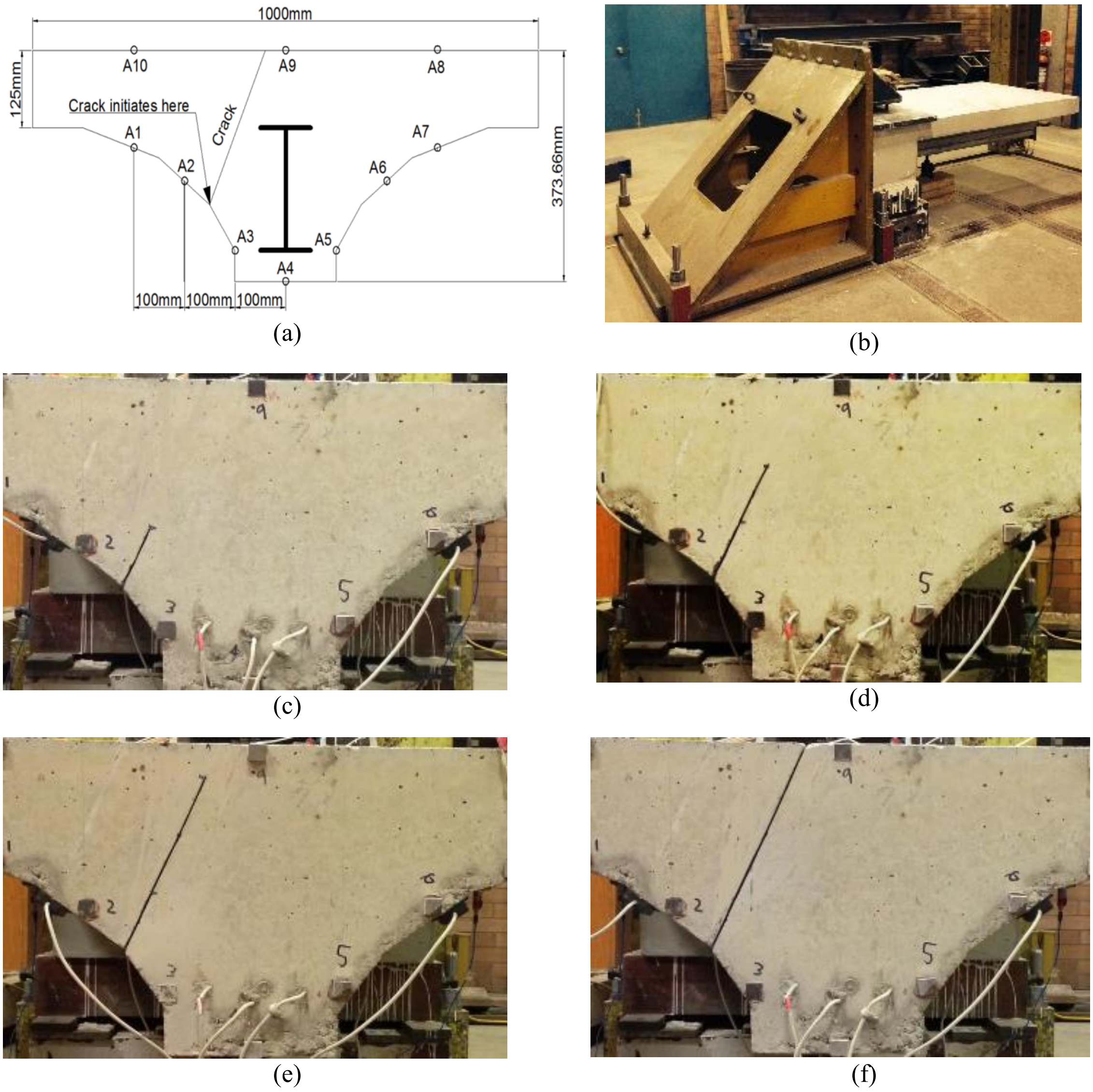

Figure 2. Test specimen: (a) intact structure with arrow indicating the cut, (b) support of the structure, (c) damage case 1: 75 mm damage cut, (d) damage case 2: 150 mm damage cut, (e) damage case 3: 225 mm damage cut and (f) damage case 4: 270 mm damage cut.

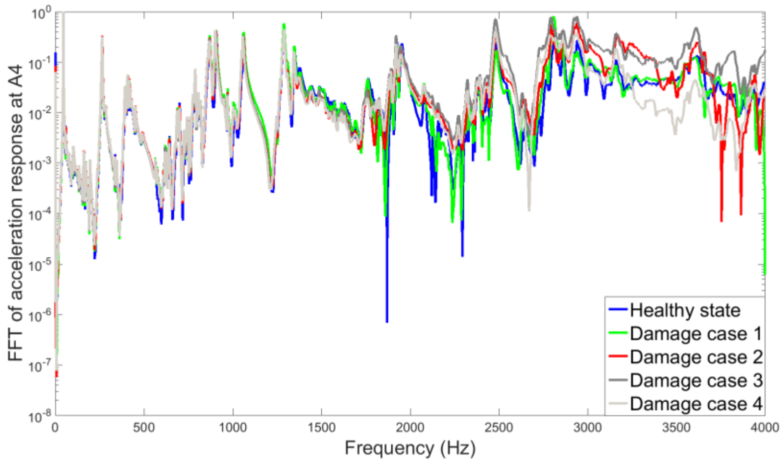

Figure 3. Comparison of the FFT of response in the healthy case and four damage cases for sensor location A4

The horizontal axis in each graph indicates the event index including 190×4= 760 events in total and each circle refers to one of these events. The vertical axis refers to the decision values. The four damage cases are differentiated by four colours. The first 190 events refer to damage case 1, the second 190 events refer to damage case 2, the third 190 events refer to damage case 3 and the last 190 events refer to damage case 4. The average of all decision values for each damage case is calculated and illustrated by a big black point. A line connects the averages of all decision values at each damage case as shown in Figure 4.

As illustrated, almost all obtained decision values are negative which indicates the fact that the testing data are not from the same class as the trained data which corresponds to the healthy state of the structure. On the other hand, it can be observed that with an increasing damage severity, an overall decrement trend in decision values is obtained, however, this is not the case for sensor A2 from damage case 1 to damage case 2. Also, it can be seen that there is very small variation in the connecting line at most sensors from damage case 3 to damage case 4 meaning that most sensors cannot detect the progress of the crack in the structure from case 3 to case 4.

From this demonstration, it can be concluded that an individually trained ML model for each sensor is able to detect the presence of damage in the structure (a negative decision value is obtained for an event from a damaged state). Moreover, the progress of the crack in the structure can also be identified for most sensors.

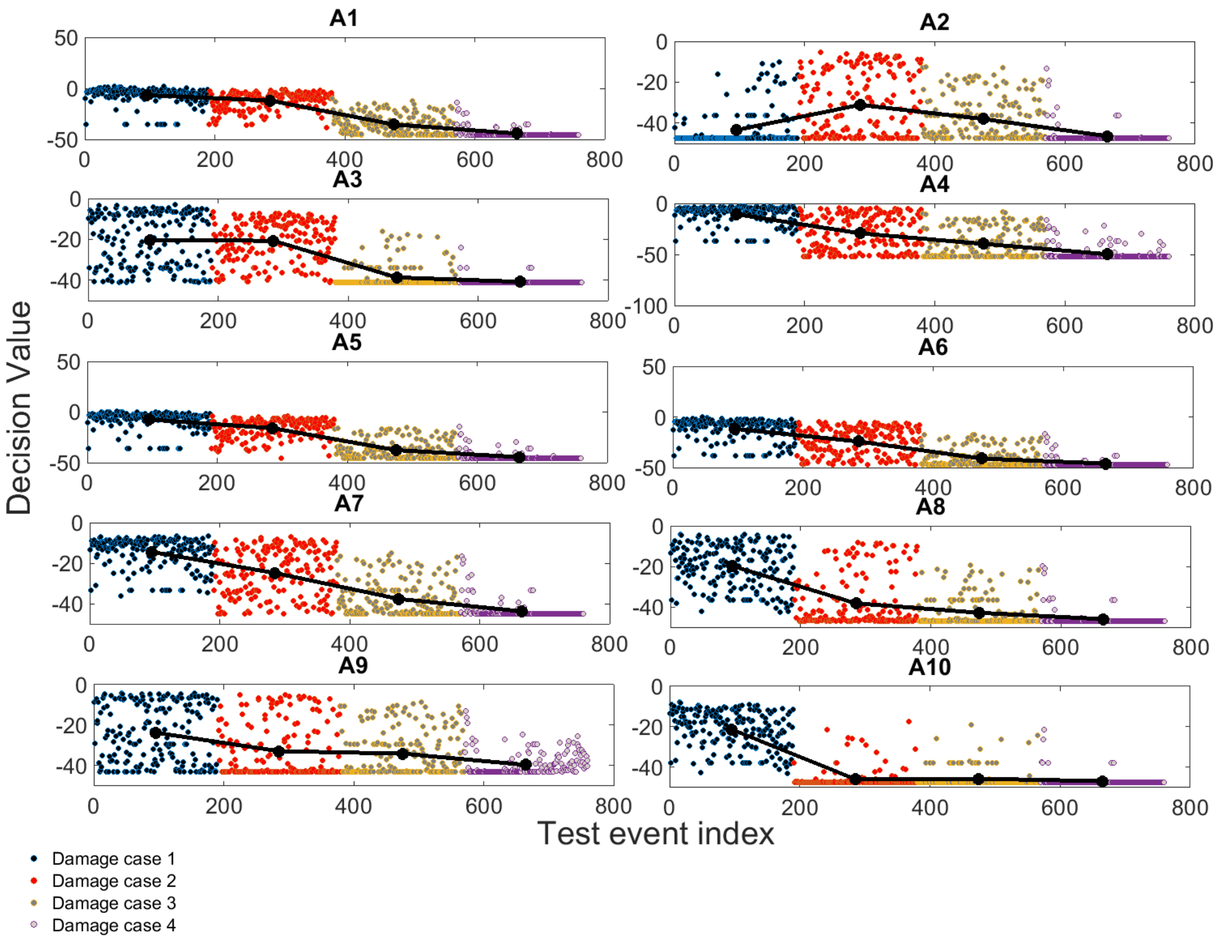

Figure 4. Damage identification results applying SVM for each sensor location

Second Approach: Implementation of SVM for All Sensor Locations

In the second exercise, the SVD approach was implemented as follows. At each frequency coordinated, the power spectral matrix was constructed. This matrix will be a 10 by 10 symmetric matrix. Then by applying SVD, the singular values of the constructed matrix were estimated for each frequency spectrum. The first and second singular values from the healthy state of the structure were utilised to train the model and then testing was conducted using the first and second singular values of each damage case. The obtained decision values are presented in Figure 5 and Figure 6 for first and second singular values, respectively. The set-up of the graphs is the same as for Figure.4.

As illustrated, almost 99% of the tested data is correctly identified as unhealthy event since the obtained decision value is negative. In addition, using this approach, the progress of damage is correctly identified as a decreasing trend in the damage index line is obtained.

This demonstration illustrates that training and testing the model using all sensor data results in a more robust indication of the crack progression in the structure. An interesting finding is that not only the first singular value can successfully assess the crack growth in the structure but also the second singular value can reliably detect its progression.

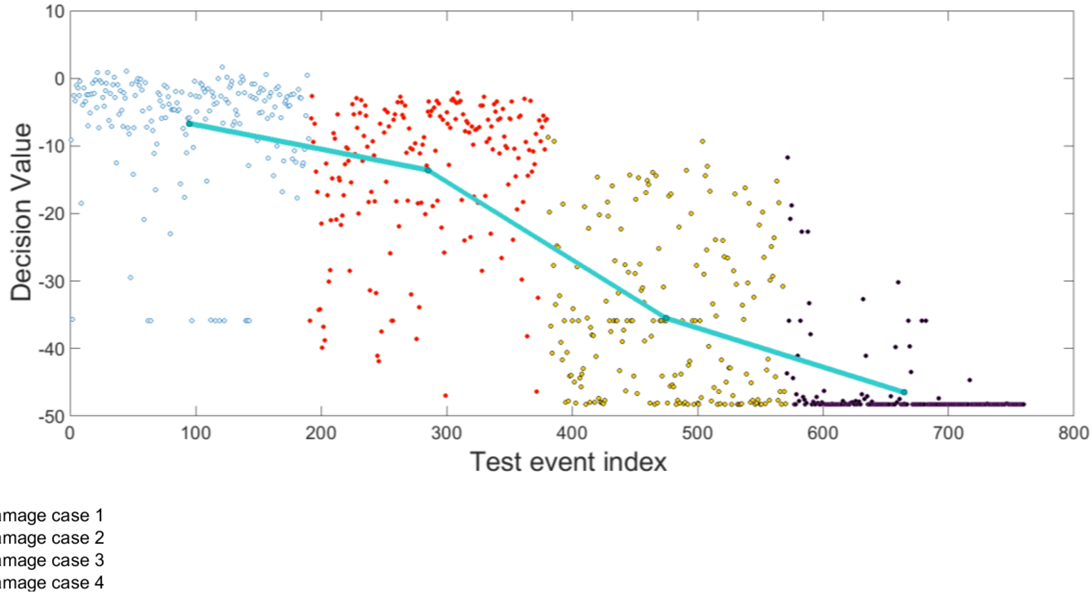

Figure 5. Damage identification results using first singular value

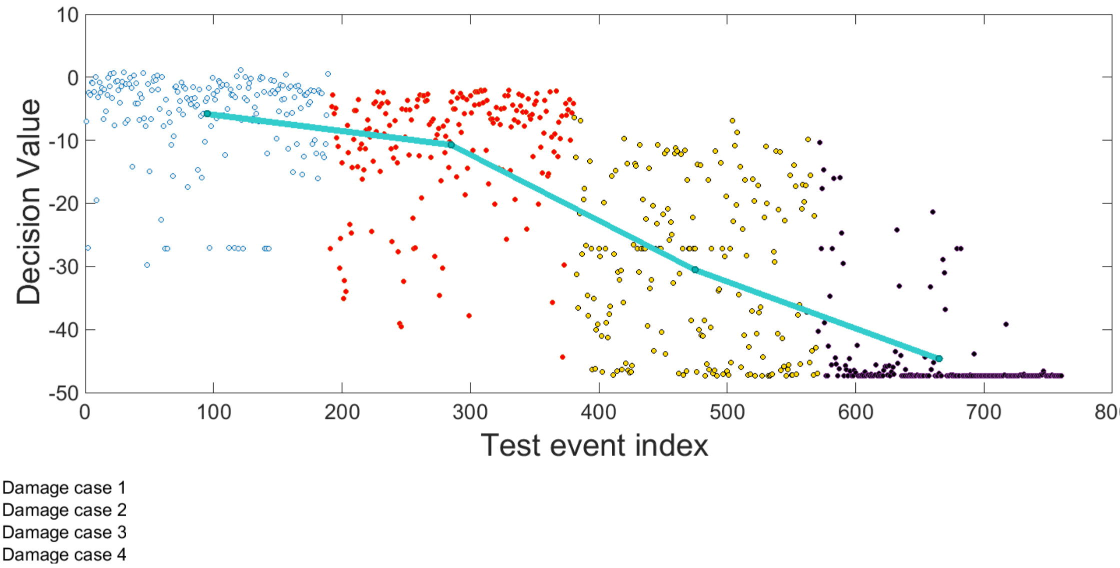

Figure 6. Damage identification results using second singular value

CONCLUSION

This work presented a damage detection methodology using a machine learning algorithm. A structural benchmark model was learnt using one-class SVM on a structural component of the Sydney Harbor Bridge and then was tested with data from damaged states of the structure. This approach suits real situations where data from a damaged state are not available for supervised learning. To demonstrate the method, an artificial damage was inflicted to the test structure and its severity was increased in four stages. Then new events were tested against the benchmark model to detect damage. Two different exercises were conducted to detect the presence and progress of damage in the structure. In the first approach, a model was constructed for each sensor location and in the second approach a model was constructed using the first and second singular value of the power spectral matrix. It was demonstrated that both approaches can reliably detect the presence of damage in the structure; however, the second approach is more superior in the detection of the crack progression in the structure. These findings indicate that the application of unsupervised learning along with the implementation of one-class SVM can provide a robust separation of two states of a structure (healthy and damaged) and can successfully evaluate the progression of damage, which is critical for structural condition assessment.

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