Characterization of Gradually Evolving Structural Deterioration in Jack Arch Bridges Using Support Vector Machine

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ABSTRACT: The main objective of structural health monitoring is to provide reliable information about the health state of the critical structures by implementing a damage characterization strategy to detect the presence of damage, location, severity as possibly failure prediction as soon as the damage occurs. This paper presents a robust approach to detect and characterize a gradually evolving damage based on time responses data captured from a steel reinforced concrete structure. The presented method is in the context of unsupervised and non-model-based approaches, hence, there is no need for any representative numerical/finite element model of the structure to be built. In this work, we propose one-class support vector machine as an anomaly detection method. One-class support vector machine fits well for damage diagnosis in structural health monitoring since there may exist many damaged patterns and one-class support vector machine can detect all of them as anomalies. To demonstrate the feasibility of the method in the detection and assessment of a gradually evolving deterioration, a test bed was established to replicate a concrete jack arch which is a main structural component on the Sydney Harbour Bridge – one of Australia's iconic structures. The structure is a concrete cantilever beam with an arch section which is located on the eastern side of the bridge underneath the bus lane. It is assumed that the structure is subjected to Gaussian white noise excitation. A crack is introduced in the structure using a cutting saw and its length is progressively increased in four stages while the depth was constant; these four damage cases correspond to less than 0.5% reduction in the first three modes of the structure. The damage identification results using the presented approach demonstrated the feasibility of applying support vector machine as a learning technique for damage characterization in structural health monitoring. The method accurately separated two states of the structure and it was also capable to identify progressively increasing damage.

1 INTRODUCTION

Structural health monitoring (SHM) is a process of damage identification (detection, localization and quantification) in a structure. It is of paramount importance for reasons associated with proper operation, increased safety, and reduced maintenance costs (Makki Alamdari et al. 2015). During last two decades, extensive research activities have been conducted on vibration-based SHM methods. Many articles have been published in this subject recently, are either in model-driven approaches or in data-driven approaches (Fan & Qiao 2011).

A typical model-driven approach in SHM adopts a numerical model of the structure, usually based on finite element analysis, which relates differences between measured data and the data generated by the model to the damage identification. However, a numerical model may not be always available in practice and does not always correctly capture the exact behavior of the real structure. On the other hand, a data-driven approach establishes a model by learning from measured data and then makes a comparison between the model and measured responses to detect damage. This approach uses techniques in pattern recognition, or more broadly, in machine learning (Worden & Manson 2007).

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 the model to new data. These characteristics help it 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. Application of supervised techniques for damage identification has been widely reported in the literature (Farrar et al. 2000). The major problem with supervised approaches is that, in practice, events corresponding to damaged states are often unavailable for supervised learning. On the contrary, unsupervised methods train the model using only healthy data and the classification problem becomes the anomaly detection problem. Data objects which significantly deviate from the normal behavior of the trained model are considered as anomalies or damage. One-class SVM is a robust technique for this purpose (Schölkopf et al. 2001).

This work is part of the efforts which have applied SHM to the Sydney Harbour Bridge. Anomalies and failure patterns of the jack arch supports are learned from the data in an unsupervised manner using one-class SVM. This suits real situations where the data for damaged state are not available for supervised learning. The learned models will be used to generate real-time health scores for every jack arch support. It avoids the time and cost of creating a numerical model and provides the flexibility of model updating. The main objective of this study is to characterize any possible damage in the jack arches using unsupervised learning. It includes detection of damage as at early stage as possible along with damage assessment to monitor its possible progression.

2 SUPPORT VECTOR MACHINE

SVM is a robust supervised learning technique. Denote $\mathbf{x}$ a feature vector extracted from sensor data, $y \in \{-1,1\}$ the label of $\mathbf{x}$, where $y = -1$ means that $\mathbf{x}$ is recorded from a damaged bridge component and $y = +1$ means that $\mathbf{x}$ 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: $f(\mathbf{x}) = sgn(\mathbf{w} \cdot \mathbf{x} - b)$ where '.' is the dot product, $sgn(x) = +1$ if $x > 0$ and $sgn(x) = -1$ otherwise. $\mathbf{w}$ and b are the parameters of the model and can be learned from a training process. Given a set of n training samples, $\{(\mathbf{x_i}, y_i)\}_{i=1}^{n}$, the training process determines the model parameters $\mathbf{w}$ and b by making sure that the classification error of the obtained model on the training set is minimized while still maximizing the margin. Mathematically, the training process is equivalent to the following minimization problem:

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

such that $y_i(\mathbf{w} \cdot \mathbf{x_i} - b) \geq 1 - \xi_i, \;\; \xi_i \geq 0, \;\; i = 1, \cdots, n,$ (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 $\mathbf{w}$ (the margin). The problem can be transformed to the dual form using Lagrangian multiplier:

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

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

This problem can be solved using quadratic programming. Once the classification model $f(\mathbf{x}) = sgn(\mathbf{w} \cdot \mathbf{x} - b) = sgn(\sum_i \alpha_i y_i \mathbf{x_i}\mathbf{x} - b)$ is learned, a health score for a new vibration record, denoted as $\mathbf{x_{new}}$, can be generated as $\sum_i \alpha_i y_i \mathbf{x_i}\mathbf{x_{new}} - b$.

3 ONE-CLASS SUPPORT VECTOR MACHINE

Due to the limitation of damaged samples available for supervised learning, unsupervised or one-class approach is more practical. In this work, we use one-class SVM as an unsupervised approach for damage detection. It assumes that all positive examples share some common properties to form one class. And negative examples can have very different properties without any commonness. It fits damage detection in structural health monitoring, since there may exist many failure patterns and one-class SVM can detect all of them as anomalies.

The algorithm in finds 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. 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. Using the settings of supervised SVM learning, the unsupervised learning process can be formed as the following optimization problem:

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

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

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 $\{\mathbf{x_i}\}_{i=1}^{n}$ 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 $f(\mathbf{x}) = sgn(\sum_i \alpha_i \mathbf{x_i x} - \rho)$. A negative health score from a new data instance will indicate it is an anomaly, which is likely damage.

4 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 Harbour Bridge. There are 800 concrete jack arches on the underside of the deck of the bus lane and it is very critical to detect any structural deterioration in the arches at as early stage 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 Harbour Bridge. The length of the specimen was 2000 mm, the width was 1000 mm and the depth was 374 mm, see Figure.1 and Figure.2.

The excitation was made using an impact hammer; it was applied on the top surface of the specimen just above the sensor A9, see Figure.1.

The response of the structure was collected by 10 uniaxial accelerometers placed in frontal face of the jack arch named A1, A2, …, A10, see Figure.1. The measurement was conducted for 2 seconds at a sampling rate of 8 kHz, resulting in 16000 samples for each event.

After testing the benchmark in a healthy condition, a crack was gradually introduced into the specimen between sensors A2 and A3 with four level of crack dimensions: (75 × 50) mm, (150 × 50) mm, (225 × 50) mm and (270 × 50) mm, see Figure.3, Figure.4, Figure.5 and Figure.6.

The responses of 190 impact tests were collected in healthy condition and in each level of damage severity.

In order to investigate the impact of damage on natural frequencies, at each damage case, a comparison was made on the measured frequency responses. Figure.7 compares the frequency response functions 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 a very small damage.

5 DAMAGE IDENTIFICATION RESULTS

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) are used since the frequency spectra will be mirrored with respect to the Nyquist frequency; hence, there are 8000 feature elements for each event.

An investigation was carried out to evaluate the suitable size for training data in order to save computational time while still maintaining the detection accuracy. The results showed that a training size of 150 randomly selected events from healthy events is adequate for training purpose.

The remaining 40 evens from the healthy state and 190 events from each damage case were used for the testing. Table 1 presents the obtained accuracy for all sensors for the healthy state testing.

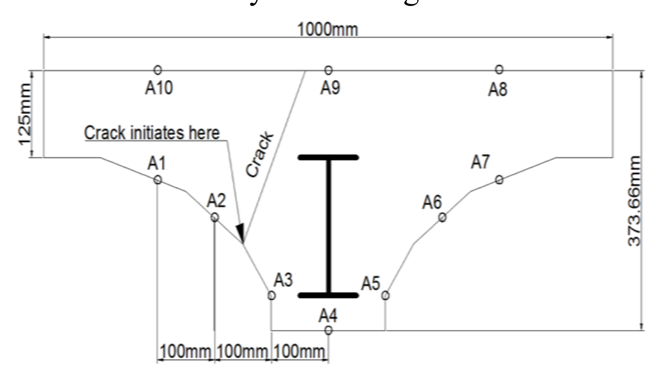

Figure 1. Test bed, intact with the arrow indicating the direction of the cut.

In order to reduce the false positive and negative rates, we used a technique called multiple testing. That is we make a decision if a joint is healthy or not based on a block of multiple sequential events. We average the joint health score based on 5 sequential events (38 blocks of 5 events) and make the decision. The false positive and negative rates are significantly reduced with multiple testing. Figure.8 to Figure.13 shows the decision values obtained by using this technique for sensors A1, A3, A4, A6, A8 and A9, respectively. As seen, events with more severe damage have lower decision values. Therefore, it suggests that we can use the decision values obtained by one-class SVM as structural health scores to evaluate the damage severity in an unsupervised manner. The same behaviour was obtained for other sensors.

Figure 2. Test bed, illustration of the cantilever at one end of the specimen.

Figure 3. Damage case 1, (75 × 50) mm cut in the concrete

Figure 4. Damage case 2, (150 × 50) mm cut in the concrete

Figure.14 presents the average of all decision values obtained from all sensors for healthy state and different damage states. As seen, the method is able to successfully separate the healthy state from the damage states and as the severity of damage increases, higher negative decision values are obtained.

Figure 5. Damage case 3, (225 × 50) mm cut in the concrete

Figure 6. Damage case 4, (270 × 50) mm cut in the concrete

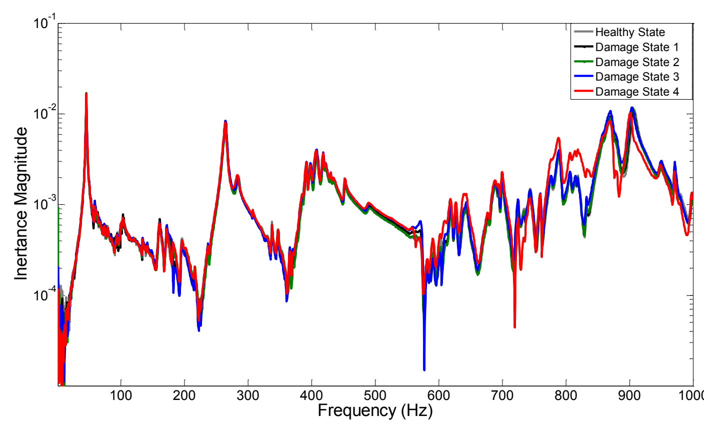

Figure 7. Comparison of the measured frequency response functions in the healthy state and four damage states.

Table 1. The accuracy of testing for all sensor locations in the healthy state

Sensor	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Accuracy (%)	92.5	97.5	100	90	95	80	90	97.5	100	95

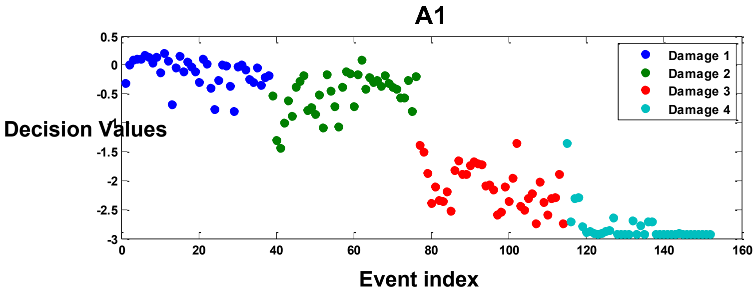

Figure 8. Damage estimation using decision values obtained by one-class SVM from sensor 1.

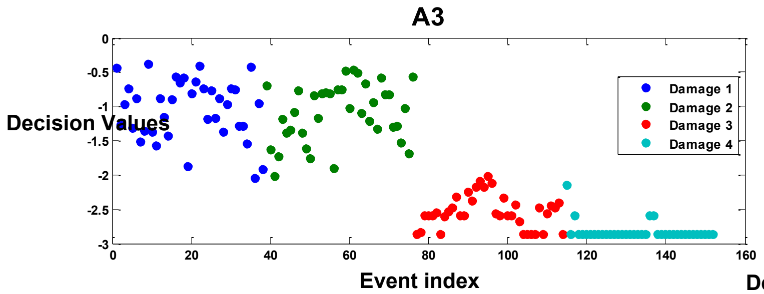

Figure 9. Damage estimation using decision values obtained by one-class SVM from sensor 3.

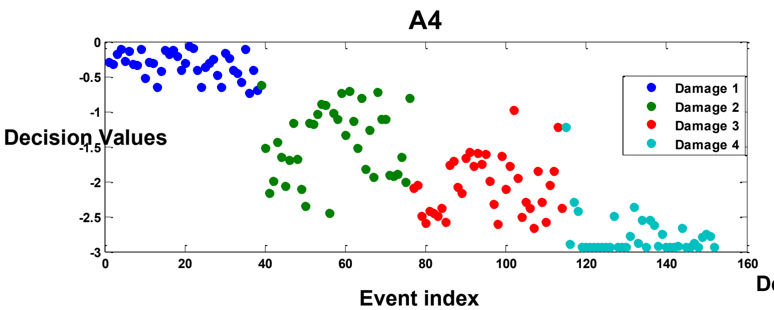

Figure 10. Damage estimation using decision values obtained by one-class SVM from sensor 4.

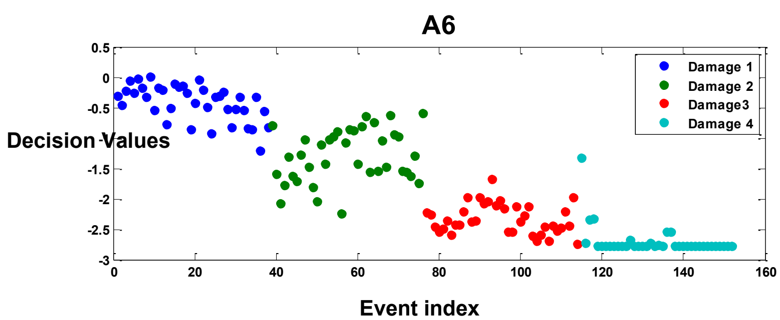

Figure 11. Damage estimation using decision values obtained by one-class SVM from sensor 6.

6 CONCLUSION

This work presented a damage detection methodology using machine learning algorithm. A structural benchmark model was learnt using one-class SVM on a structural component of the Sydney Harbour Bridge. This approach suits real situations where the data for damaged state are not available for supervised learning. An artificial damage was created in the structure and its severity was increased in four stages. Then new events were tested against the benchmark model to detect damage. The approach was shown to work very well to identify a progressively increasing crack in the structure. It was demonstrated by using unsupervised learning and implementing one-class SVM, we are able to detect damage by separating two states of the structure and successfully evaluate the progression of damage.

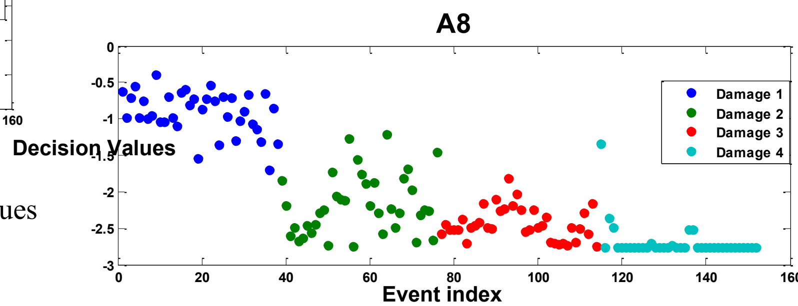

Figure 12. Damage estimation using decision values obtained by one-class SVM from sensor 8.

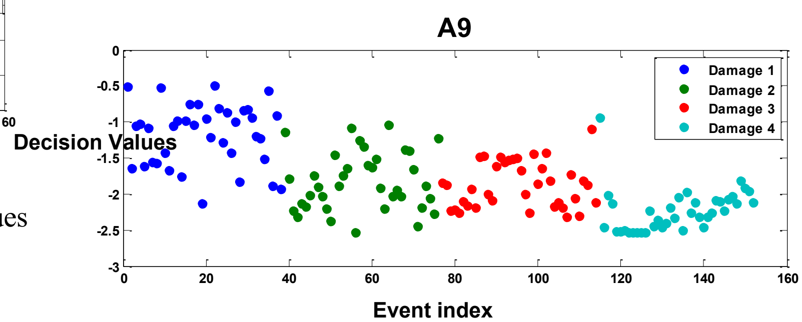

Figure 13. Damage estimation using decision values obtained by one-class SVM from sensor 9.

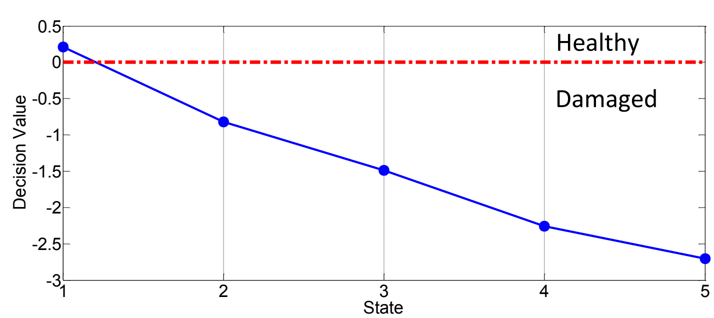

Figure 14. Damage detection using decision values of all test events.

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