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UNSUPERVISED NOVELTY DETECTION BASED STRUCTURAL DAMAGE DETECTION METHOD

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ABSTRACT

Many structural damage detection methods using machine learning algorithms and clustering methods have been proposed and developed in recent years. Novelty detection is a common method that is based on an unsupervised learning technique to detect structural damage. The detection process involves applying the novelty detection algorithm to recognize abnormal data from the testing data sets. In order to make these algorithms capable of identifying abnormal data, sufficient normal data must first be obtained and used as training data. It is the fact that sufficient normal data is relatively convenient to measure compared to abnormal data for large-scale civil structures. Abnormal data from the testing data sets can be identified by using the well-trained normal model established by the algorithms. In this paper, a machine learning based novelty detection method called the Density Peaks based Fast Clustering Algorithm (DPFCA) is introduced and some improvements to this algorithm are made to increase the precision of detecting and localizing the damage in an experimental structure. Feature extraction is also an important factor in the process of damage detection. Thus, two damage-sensitive features such as crest factor, and transmissibility are extracted from the measured responses in the experiments. Experimental results showed good performance of the innovative method in detecting and locating the structural damage positions in various scenarios.

Keywords: novelty detection, damage detection, abnormal data, density peaks, fast clustering

1. INTRODUCTION

During the last two decades, numerous structural damage detection methods have been developed to prevent sudden collapses of civil infrastructures due to continuously repeated loading, overloading, deterioration, aging, and damaging hazardous loads. One of the popular approaches to the detection of damage in structures is using the vibration-based damage detection methods. The vibration-based methods are broadly classified as physics model-based approaches and data-based approaches (Farrar and Worden 2012, Barthorpe 2010). The data-based approaches are more frequently selected as damage detection methods due to the possibility of quasi real-time detection of damage. These data-based approaches use statistical or probabilistic methods, such as supervised and unsupervised machine-learning algorithms, pattern recognition algorithms, and clustering methods to differentiate damage-sensitive features calculated from dynamic measurements from sensors installed on the 'intact' and 'damaged' structures (Sohn et al. 2002). Supervised learning approaches require data from both intact and damaged structures to do the training work. However, data for various damage scenarios in real civil structures is typically quite scarce (Park at al. 2010). Therefore, unsupervised learning approaches are preferred for novelty detection as the training process requires the data from 'intact' structures only (Ding et al. 2014). Thus, unsupervised novelty detection methods using machine-learning and clustering methods have been widely applied to the detection of damage in civil structures in recent years. For example, (Yeung and Smith 2005) applied two unsupervised learning artificial neural network (ANN) algorithms, the Probabilistic Resource and Allocating Network (PRAN) and the DIGENT network, to detect the loosening of joints in the girders of a finite element model of an historic suspension bridge. The results showed that a damage identification rate of about 70% can be achieved while striking a balance between sensitivity and misclassification of the neural networks. (Roy et al. 2014) presented a novel damage detection model based on the unsupervised learning technique to detect and locate the induced damage in a thin aluminum plate. A neural network-based sparse auto-encoder algorithm was integrated with statistical outlier analysis in this novelty detection approach. The experimental results showed that the proposed approach can separate intact and damaged data with good accuracy. The shortcomings of this algorithm are: (1) the assumed Gaussian distribution may not be appropriate for all cases, and (2) there is no parametric density estimate or extreme value statistic (EVS) to train the model to improve outlier detection performance. (Oh and Sohn 2009) used an unsupervised support vector machine (SVM) incorporated with a discrete-time prediction model to detect the damage in a mass-spring structural system in the laboratory. The results of this experiment demonstrated that the proposed method is effective in detecting structural damage under an unknown level of a time-varying excitation condition. (Khoa et al. 2014) used one-class support vector machine (OCSVM) to detect and locate the damage position in a laboratory-based building structure and the Sydney Harbour Bridge. The results showed that the detection accuracies were lower than that of the supervised algorithm used in the paper. (Gul and Catbas 2009) presented a novel time series analysis methodology to detect, locate and qualify the structural damage in a numerical four-degree of freedom structural system. In this method, an Auto-Regressive model with eXogenous inputs (ARX) model was created using the data from the intact structure to predict the data from the damaged structure. The results of the experiment showed great performance of the proposed method in damage detection. (Santos et al. 2015) presented a novel data-driven strategy based on unsupervised learning algorithms, such as principle component analysis, symbolic data analysis and cluster analysis, to detect stiffness reduction in the numerical model of a cable-stayed bridge. From the analysis, it was observed that the proposed strategy was able to detect a stiffness reduction as small as 1% in a stay cable. (Toivola and Hollmen 2009) improved a naive Bayes classifier to create a probabilistic model for novelty detection and applied this model to detect the damage in a wooden bridge structure in laboratory conditions. The results indicated that the proposed method was able to detect damages in the bridge in most cases. However, according to the fact that there was a 71% true positive ratio of the results in the best condition, the damage detection performance still needs to be enhanced to increase the detection accuracy.

Based on the above literature review, the majority of structural damage detection methods at present can easily give rise to errors in locating the position of the actual damage site. In addition, most of the research was conducted using numerical simulation which causes lack experimental verification in the laboratory or through field tests. This paper proposes an innovative unsupervised novelty detection-based damage detection method using a density peaks-based fast clustering method (Rodriguez and Laio 2014), and validates the performance of this method with experimental studies using a lab-scale steel structure in a damage scenario.

2. METHODOLOGY: DENSITY PEAKS-BASED FAST CLUSTERING

In order to make damage detection for the experimental structure in this paper, the density peaks-based fast clustering algorithm (DPFCA), which was originally developed by (Rodriguez and Laio 2014) as a novelty detection approach for cluster analysis, is developed for an unsupervised novelty detection-based damage detection method. The original DPFCA is developed based on the combination of density-based and distance-based techniques, and it can detect and form the non-spherical distribution clusters and automatically find an appropriate number of clusters. The most important advantage of this algorithm is that it can identify the halo points that surround the formed clusters. Here, the halo points can be seen as the scattered novelty points of the clusters. This ability of identifying novelty points helps to make improvements seen in the following algorithm steps to realize novelty detection based on the unsupervised training technique.

The principle of DPFCA is to find the appropriate density peaks of clusters and to realize fast clustering. There are two basic assumptions of this algorithm. The first assumption is that a relatively large number of point neighbors with lower local density are nearby to the cluster density peak points. And the second one is that each cluster density peak point has a relatively large distance from other cluster density peak points. The steps of this algorithm are as follows:

Step 1. Calculate local density, ρ_i, of each data point i, which is defined as:

[1] $$\rho_i = \sum_j \& (d_{ij} - d_c)$$

where &(x)= 1 if x < 0 and &(x)= 0 otherwise, d_c is the predefined cut-off distance, and d_{ij} is the distance between point i and point j. Some improvements are made in this algorithm in order to improve the performance of the algorithm on the damage detection abilities in the case study. The first improvement is introducing the Gaussian kernel function of radius (Benoudjit et al. 2002) to calculate the local density of the data points. The expression of the Gaussian kernel of radius is as follows:

[2] $$\rho_i = \sum_j \exp[\ (d_{ij} - d_c)^2]$$

The second improvement is that the Mahalanobis distance metric (Xiang et al. 2008) is applied to measure the mutual distances of the data points instead of the classical Euclidean distance metric. The reason for this distance measurement adjustment is that Mahalanobis distance is unitless and takes into account the correlations of the data set by their covariance matrix. Thus, this distance metric is widely used in cluster analysis and classification techniques.

Step 2. Calculate the distance, δ_i, of each data point, i. Here, δ_i is defined by the minimum distance between the point i and any other point with higher local density:

[3] $$\delta_i = \min_{j:\rho_j > \rho_i} (d_{ij})$$

We take $\delta_i = \max_j (d_{ij})$ for the point with highest local density.

Step 3. Select some of the points with an anomalously large δ_i and relatively higher local densities as cluster density peak points. This step is the core of the algorithm, which makes sure the clusters have enough data points and the cluster density peak points are relatively far away from each other.

Step 4. After the cluster density peak points are selected, assign each of the remaining points to the same cluster as its nearest neighbor with higher local density.

Step 5. In order to find halo points in each of the formed clusters, border regions of these clusters should be defined by introducing the previous cut-off distance, d_c. If the set of points are assigned to that cluster, but being within a distance d_c from data points belonging to other clusters, that set of points is the border region of that cluster. The point with the highest density within each border region, ρ_b, can be found out. Then, the halo points in each cluster are defined as $\rho_i < \rho_b$. So, if there is any point with lower local density compared with ρ_b, that point is assumed to be a halo point. The halo points are also called novelty points.

Step 6. Once the border regions appear, compute the average value of ρ_b for all clusters and define it as the threshold of local density, ρ_c, which will be used to detect the novelty points in the following testing process. However, this procedure sometimes does not detect novelty points because of the short cut-off distance d_c, which was predefined in Step (1). Thus, the cut-off distance d_c used in Step (5) should be updated to detect novelty points that may be identified based on engineering judgement from the plotting of the clusters. To find the appropriate value of the cut-off distance, trials and errors are required by going back to Step (5). To update the cut-off distance, weight, w, is introduced and expressed as wd_c, which is only used for Step (5) and (6). These trials and errors to detect novelty points in normal data are the training procedure for this proposed algorithm.

Step 7. After these formed clusters are trained, each testing point can be added into this well trained model separately to calculate their local densities and compare them with the threshold value, ρ_c. The testing point is identified as a novelty point once the local density of a specific testing point is lower than ρ_b.

3. DAMAGE SENSITIVE FEATURES

Feature extraction refers to the process of selecting the features to be used in the damage detection process from the measured data. Ideal features are sensitive to the presence of damage in the structure, and at the same time are insensitive to operational and environmental variability in a normal range in the damage detection. In this paper, acceleration data from the sensors attached to the joints of the lab-scale steel structure were used to extract the damage sensitive features. The raw acceleration data was first processed into several kinds of damage-sensitive features. Then, the different kinds of features were combined into multi-dimensional feature vectors. Here, each feature vector corresponds to the response of each joint for each experimental test. Two different features were calculated in this paper: one is crest factor and the other is the integral of a transmissibility function.

3.1 Crest factor

The first feature is the crest factor of acceleration time series, $a(t)$, comprised of *n* discrete points. This feature has been verified to be sensitive to the structural damage (Farrar and Worden 2012) and it can be obtained by the following equation:

[4] $$C = \frac{|a|_{peak}}{a_{rms}}$$

where $|a|_{peak} = \max|a(t_n)|$; $a_{rms} = \sqrt{\frac{1}{n}\sum_n (a(t_n))^2}$.

3.2 Transmissibility

The second feature is the integral of the transmissibility curve between one-frequency intervals on the spectrum (Long and Buyukozturk 2014). This frequency window corresponds with resonant modes of the structure. The resonant frequency information can be identified by checking a frequency spectrogram. The spectrum can be obtained using a Fourier transform of the raw acceleration response signals.

The transmissibility is defined as the Fourier spectrum of the response at a degree of freedom (DoF) divided by the Fourier spectrum of the reference response at a DoF (Schwarz and Richardson 2004). The reference response is a measurement taken at the same DoF for all of the measurements of transmissibility. In order to obtain a good transmissibility signal, the reference DoF should be chosen at a DoF where the structure has a high magnitude of motion. The resulting measurement indicates the motion of each roving DoF normalized by the motion of the reference DoF. The expression of the transmissibility response can be formulated as:

[5] $$T_{ij}(\omega) = \frac{F_i(\omega)}{F_j(\omega)}$$

where ω is the frequency of the Fourier spectrum, $F_i(\omega)$ is the Fourier spectrum of the response at a DoF, and $F_j(\omega)$ is the Fourier spectrum of the reference response at the selected DoF.

Then, the aim is to reduce the dimensionality of the feature, because many of the feature dimensions do not provide useful information on the state changing of structures. It is important to notice the fact that the transmissibility may be more sensitive at resonant frequencies of the structure. Thus, by checking the Fourier transforms of some representative DoFs, some resonant frequencies can be identified. Then, the identified resonant frequencies of interest can be used to obtain the integral of the transmissibility function in the narrow window around this frequency. The extracted feature for the resonant mode at frequency ω is given by:

[6] $$I_i = \int_{\omega\ \Delta\omega}^{\omega+\Delta\omega} T_{ij}(\omega)$$

where $\Delta\omega$ is the half length of the selected frequency window that contains the identified resonant frequency, $T_{ij}(\omega)$ is the transmissibility function, and I_i is the integral of the transmissibility function.

4. EXPERIMENTAL SETUP

4.1 Experimental lab-scale steel structure

In order to demonstrate the effectiveness of the proposed damage detection algorithm described above, a lab-scale steel structure was used for experimentation (Cha and Buyukozturk 2015). A configuration of a three-story and two-bay steel structure was tested in the laboratory. The dimensions of the columns in this structure were 0.60 m × 0.0508 m × 0.0064 m and the beams of this structure were of the same dimension and material as the columns. The structural components were bolted together at each joint with four bolts and the entire structure was bolted to a heavy concrete foundation as a reaction mass, shown in Figure 1. The measured natural frequencies of intact structure are 3.4, 8.2, 8.6, 10.6, and 18.4 Hz.

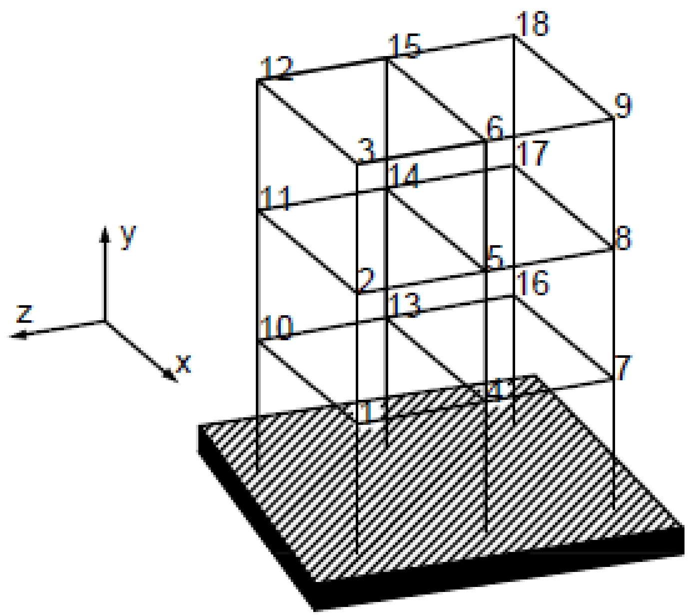

Figure 1: Experimental setup and structural joints locations

4.2 Damage scenario

Triaxle IEPE piezoelectric acceleration sensors were used to measure the vibration of the steel structural model. The sensors were attached to the column components adjacent to the structural joints. The sensor at each joint gives acceleration time signals of the three-directions with a 6 kHz sampling rate. To excite the structure, a small shaker attached to the top corner of the structure (close proximity to Joint 18) was used, which provided a random white Gaussian noise in a frequency range of 5–350 Hz in the flexible *x* direction, shown in the Figure 1. For the intact structure, all four bolts at each joint were tightened. There is a damage scenario involving severely loosened bolt connection at joint 9. The structure was tested 60 times for the intact scenarios and 10 times for the damage scenario (DS). The damage scenarios and test numbers are summarized in Table 1.

Table 1: Damage scenarios and locations

Damage Scenarios	Number of Tests	Damage types
Intact	1-60	No damage
DS	61-70	Four bolts loosened at Joint 9

5. CASE STUDY

In order to calculate two damage sensitive features, raw acceleration signals in the flexible x direction of the structure was measured, and two-dimensional feature vectors were extracted from the measurements. The first principle component of the feature vector is the crest factor, and the second one is the integral of the transmissibility function between 40 and 50 Hz, because a resonant frequency is identified from this selected frequency window by examining some representative spectrums. The damage detection results are shown in Table 2. The values of the minimum of ρ , and minimum of of δ , in Table 2 are the thresholds of local density of each point and the mutual distance δ of each point, respectively. These two parameters are determined by checking the formed decision graphs in order to select appropriate cluster density peak points in the decision graphs. In this case study, the values of d_c listed in Table 2 are used to calculate the local density of points in Step (1) in section 2. Because d_c is the predefined parameter, it is defined as the highest 2% of the entire mutual distances, d_{ij}, for this case study. The value of 2% is determined based on various case studies. The weight, w, of the cut-off distance, wd_c , in the table is used to find the border regions of the formed clusters to train the intact model. The value for the detection rate of one joint indicates the possibility that damage happened at that joint. For example, the detection rate of Joint 1 in Damage Scenario (DS) is 0.2, as shown in Table 2, means that two of the 10 testing damage points from Joint 1 are detected as novelty points by the trained intact model. According to the detection rates as shown in the Table 2, the induced damage is localized to the Joint 9 which is the exact damaged joint and Joint 5 which is adjacent to the Joint 9 with highest detection rate 0.9. Even though this structure is small and vibrations are easily propagated through the entire structure with densely installed sensors (Long and Buyukozturk 2014), the proposed method is able to localize the damage properly.

Table 2: Rate of damage detection with the method of DPFCA

Joint	Minimum of ρ	Minimum of δ	Calculated d_c	Weight w	Detection Rate
1	1.5	0.5	0.26	1.1	0.2
2	2.0	0.3	0.20	1.1	0.1
3	1.5	0.5	0.21	1.4	0.6
4	1.5	0.5	0.20	1.6	0.7
5	1.5	0.5	0.15	1.8	***0.9***
6	1.5	0.5	0.18	2.1	0.8
7	1.5	0.5	0.13	1.4	0.3
8	1.5	0.5	0.17	1.4	0.3
9	1.0	0.5	0.10	2.8	***0.9***
10	1.5	0.5	0.21	1.0	0.7
11	1.5	0.5	0.26	1.4	0.6
12	1.5	1.0	0.24	1.3	0.7
13	1.5	1.0	0.18	1.9	0.8
14	1.5	0.5	0.27	1.4	0.5
15	1.5	0.5	0.20	1.4	0.2
16	1.5	0.5	0.18	1.4	0.4
17	1.5	0.5	0.14	1.8	0.2
18	1.5	0.5	0.09	3.6	0.1

In order to explain the detailed damage detection procedure of DPFCA, a detection example for one joint is presented. The decision graph for selecting density peak points at Joint 9 is presented in Figure 2. The two large points with two colors, blue and magenta, in the figure are selected as the appropriate cluster density peak points. The ranges of selection of the cluster density peak points are ρ >1.0 and δ >0.5 based on examining the decision graph to make sure that the selected points should have relatively large δ and high ρ compared to other points, which is explained in Section 2 Step (3).

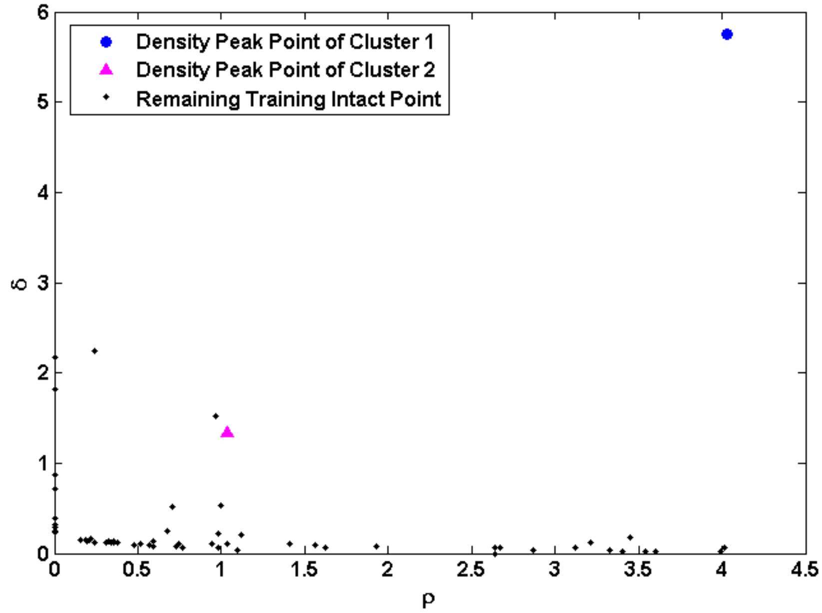

Figure 2: Decision graph of the density peak points selection for clusters at Joint 9 for Damage Scenario

Figure 3 shows the clustering condition of the 60 intact points from Joint 9. In the training process, two clusters are formed based on the two selected cluster density peak points in the previous step, as shown in Figure 2. By increasing the weight, w, of the cut-off distance, $w\,d_c$, the halo points shown in Figure 3 are identified, which is illustrated by Step (6) in Section 2. The halo points shown in Figure 3 can be seen as the novelty points of the intact points. In addition, a threshold of local density, ρ_c, is calculated by averaging the values of ρ_b of the two formed clusters, as explained in Section 2 at Step (6).

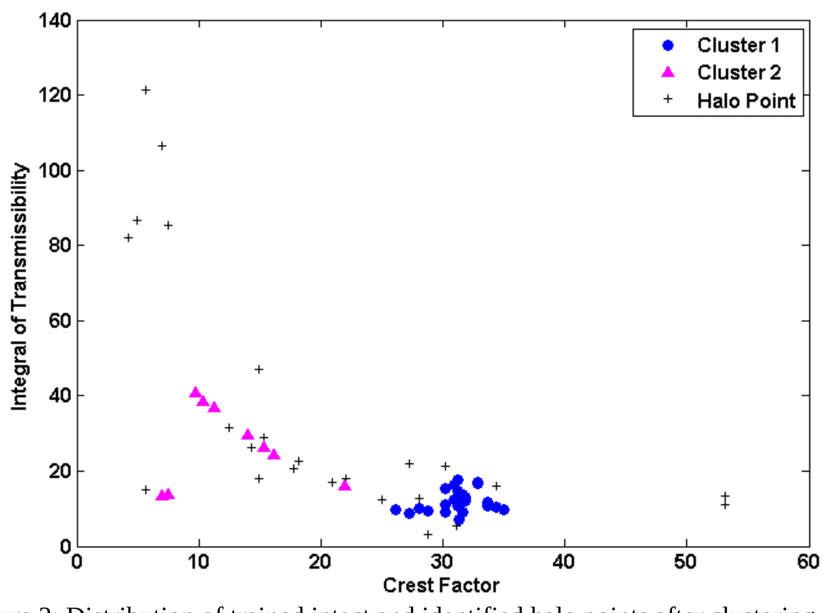

Figure 3: Distribution of trained intact and identified halo points after clustering

In Figure 4, ten testing damage points from Joint 9 in Damage Scenario are added into the well-trained intact dataset model separately and their local densities, ρ_t, are calculated taking into consideration the previous 60 intact points, as shown in Figure 3. By comparing the testing points' local densities, ρ_t, with the above obtained threshold of local density, ρ_c, nine points with a lower local density than ρ_c are identified as damage points and can be seen as novelty points in Figure 4. Thus, the detection rate of Damage Scenario is 0.9. In order to show the distribution of the ten testing damage points with the trained intact model, as shown in Figure 3, the identification results of ten independent novelty detections for each of testing damage points are combined together and are shown in Figure 4.

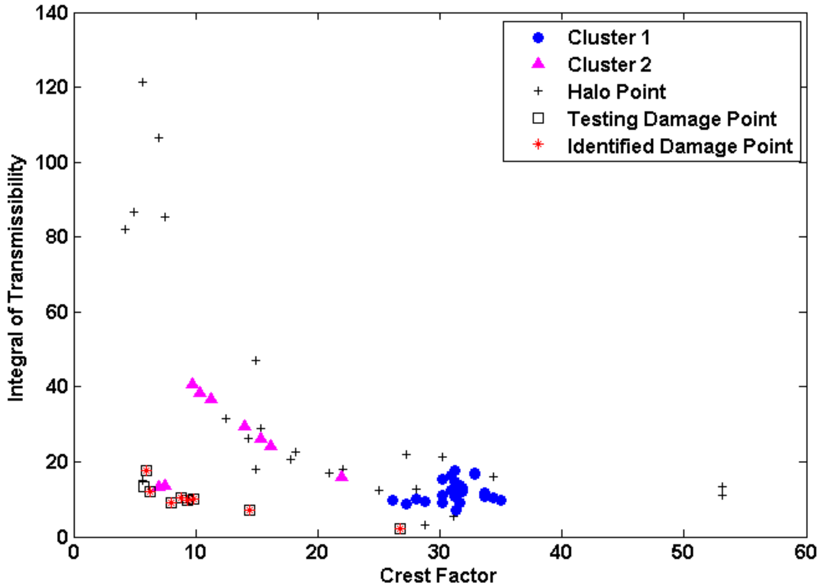

Figure 4: Distribution of identified damage points by the trained intact model and testing damage points

The proposed novelty detection method in this paper performs very well in structural damage detection and shows effectiveness in localization of the damage positions in structures. As an unsupervised learning method, DPFCA uses only measured data from the intact structure to train the damage detection algorithm. The overall damage detection process is quite fast, with high computational cost efficiency due to the advantages of the original fast clustering algorithm. Thus, DPFCA has a high possibility of application to the real-time monitoring of damages in civil structures. Based on the analysis of the damage detection results in the case study, the improved DPFCA performs very well on locating the damage position in the damage scenario. However, due to the limited volume of the intact training dataset, intact models were not trained very well in some cases. In addition, because there are only 10 damage testing datasets in the damage scenario, the rate of damage detection achieved an identical detection rate at only a few points. It is possible to calculate the possibilities of the potential damage positions at the structural joints when the volume of the testing dataset is increased.

6. CONCLUSIONS

An innovative novelty detection method, density peaks-based faster clustering algorithm (DPFCA), is proposed to detect structural damage. In order to increase the accuracy of damage detection in this method, the Gaussian kernel function of radius and the Mahalanobis distance metric were applied to compute the local densities of the points and measure their mutual distances. In addition, in order to develop this method as a structural damage detection method, the DPFCA was modified by adding a threshold of local density to the intact training model in order to identify the novelty points of the testing damage points. This proposed damage detection method used crest factor and transmissibility as damage sensitive features, which were extracted from the measured data of acceleration sensors installed in a lab-scale steel structure. The experimental results showed that the improved DPFCA achieved good performance of damage detection, especially locating the structural damage position. In summary, valuable information was obtained by the improved DPFCA to locate the damage position in the steel structural model in the laboratory. Even though the damage detection method using the improved DPFCA presents superior performance for damage localization, more research effort could be invested to improve its computational efficiency, such as reducing the workload of artificial parameter setting and increasing the training effectiveness using a larger volume of the experimental dataset. So, ongoing development in research may improve the algorithm of the improved DPFCA to increase the automation of this novelty detection method.

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