Output-only structural health monitoring based on mean shift clustering for vibration-based damage detection

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Abstract
Damage assessment based on vibration response measurements from engineering structures has been an essential research area in the structural health monitoring field. Vibration signals are often available and can be measured from different types of monitoring systems through a diversity of data acquisition systems and sensors. Based on suitable data treatment, valuable information from the structural dynamics can be extracted and used as damage-sensitive features for detecting early and progressive structural damage, thereby increasing safety and avoiding collapses. However, the operational and environmental variations often arise as undesired effects in the damage-sensitive features, which might negatively influence the proper identification of damage. To deal with this drawback, this paper presents an output-only technique based on mean shift clustering (MSC) to automatically discover an unknown number of clusters that correspond to the normal and stable state conditions of a structure. Unlike most methods in the literature, MSC is a nonparametric technique that does not require prior knowledge of the number of clusters and can identify clusters of distinct shapes, sizes and density. The superiority of the MSC technique, over the state-of-the-art ones, is tested by applying a damage detection strategy implemented through the Euclidean distance, which permits one to locate the outlier formation in relation to the chosen data clusters, using data sets from the Z-24 Bridge in Switzerland.

1. INTRODUCTION
Damage detection based on vibration response measurements from engineering structures has been a crucial research area in the structural health monitoring (SHM) field [1, 2]. Vibration signals are often available and can be measured from different types of monitoring systems through a diversity of data acquisition systems and sensors. Based on suitable data treatment, valuable information from the structural dynamics can be extracted and used as damage-sensitive features for detecting early and progressive structural damage, thereby increasing safety, avoiding collapses and supporting the decision making process regarding maintenance, repair, and rehabilitation.

Unfortunately, operational and environmental variations (e.g., temperature, operational loading, humidity and wind speed) often arise as unwanted effects in the damage-sensitive features and usually mask changes caused by damage, which might negatively influence the proper identification of damage [3]. To deal with this drawback, several machine learning algorithms with different working principles have been proposed to mitigate (or even remove) these effects on the extracted features as well as to separate changes in damage-sensitive features caused by damage from those caused by varying operational and environmental conditions [4–9]. These approaches are often characterized as unsupervised
and output-only because they are trained only with damage-sensitive features related to undamaged condition without any measurement directly related to operational and environmental parameters.

In [7] and [10], an approach based on the Gaussian mixture model (GMM) is applied to model the main clusters that correspond to the normal state conditions of a bridge. The damage detection is performed on the basis of an outlier formation regarding the chosen clusters of main states. Although this approach has revealed better damage detection performance when compared to other traditional methods, it assumes Gaussian distributions which may compromise the reliable estimation of clusters. As an alternative, the Fuzzy c-means (FCM) approach is used in [11] and [12] to distinguish between undamaged and damaged state conditions. However, this approach can not assess the damage severity in a clear manner and often produces a significant number of false-negative indication of damage, as demonstrated in [11]. K-means clustering is also a possible approach to identify the normal condition of a structure in terms of a finite number of clusters and then classify new unknown state conditions. Despite this approach was used in [9] and [13, 14] with relative success, its applicability is limited due to the stochastic behavior and invariant shapes of clusters.

Therefore, this paper presents an output-only technique based on mean shift clustering (MSC) [15] to automatically discover an unknown number of data clusters that correspond to the normal and stable state conditions of a structure. Unlike most methods in the literature, MSC is a nonparametric technique that does not require prior knowledge of the number of clusters and can identify clusters of distinct shapes, sizes and density [16]. As long as the main stable state conditions of the structure are determined, the superiority of the MSC approach, over the state-of-the-art ones based on K-means, FCM and GMM, is tested by applying a damage detection strategy implemented through the Euclidean distance (ED), which permits one to locate the outlier formation in relation to the chosen data clusters, using data sets from the Z-24 Bridge in Switzerland. The classification performance is assessed on the basis of Type I (false-positive indication of damage) and Type II (false-negative indication of damage) error trade offs.

The remainder of this study is organized as follows. In Section 2, the MSC approach is derived to determine the health state of a structure based on a reliable estimation of data clusters. Section 3 describes the Z-24 structure, the long-term vibration data, and the major environmental influence. In Section 4, the experimental results on extracted damage-sensitive features from the test structure are discussed and a comparison with state-of-the-art approaches is also emphasized. Finally, Section 5 synthesizes the main strengths and limitations of the MSC approach.

2. DAMAGE DETECTION BASED ON MEAN SHIFT CLUSTERING

This section presents the methodology of the MSC approach, which is divided into two steps. First, the estimation of data clusters through MSC is presented. Second, the damage detection strategy based on the ED is described taking into account the main data clusters estimated in the first step.

For general purposes, one may assume a training data matrix, $X \in \mathbb{R}^{m \times n}$, with $n$-dimensional feature vectors from $m$ different operational and environmental conditions when the structure is undamaged and a test data matrix, $Z \in \mathbb{R}^{l \times n}$, where $l$ is the number of feature vectors from the undamaged and/or damaged conditions.

2.1 Estimation of data clusters

MSC seeks to discover modes or clusters in a smooth density of observations [15, 16]. This algorithm is a centroid-based method, which works by updating candidates for centroids to be the mean of the observations within a given region. Afterwards, these candidates are filtered in a post-processing phase to eliminate redundancies to form the final set of centroid.

Given a candidate centroid $x_i$ for iteration $t$, the centroid is updated according to

$$x_i^{t+1} = x_i^t + \lambda \left( x_i^t \right).$$  (1)
where $\lambda (x')$ is the mean shift vector that is computed for each centroid located in a region of the maximum increase in the density of observations.

Assuming $m$ observations $x_i$ on an $n$-dimensional space $\mathbb{R}^n$ and the associated diagonal bandwidth matrices $h_i I_{m \times m}$, $i = 1, \ldots, m$, the observation density estimator obtained with the kernel profile $k(x)$ is denoted by

$$f(x) = \frac{1}{m} \sum_{i=1}^{m} \frac{1}{h_i} k \left( \frac{x - x_i}{h_i} \right).$$

(2)

Herein, the multivariate normal profile is considered such as

$$k(x) = e^{-\frac{1}{2} x' x} \quad x \geq 0.$$  

(3)

By computing the gradient of Equation (2), the stationary observations of the density function satisfy

$$\frac{2}{m} \sum_{i=1}^{m} \frac{1}{h_i^{n+2}} (x_i - x) g \left( \frac{x - x_i}{h_i} \right) = 0,$$

(4)

where $g(x) = -k'(x)$. The solution of Equation (4) is a local maximum of the density function which can be iteratively reached applying mean shift procedure, i.e., effectively updating a centroid to be the mean of the observations within its neighborhood

$$\lambda (x) = \frac{\sum_{i=1}^{m} \frac{x_i}{h_i^{n+2}} g \left( \frac{x - x_i}{h_i} \right)}{\sum_{i=1}^{m} \frac{1}{h_i^{n+2}} g \left( \frac{x - x_i}{h_i} \right)} - x,$$

(5)

where $x$ is the current mean, $\lambda (x)$ is the mean shift vector and $g(\cdot)$ is the kernel function that uses a bandwidth parameter $h$ for multivariate kernel density estimation. The Gaussian and Epanechnikov kernels are the options most commonly used in a large range of applications [17, 18]. In this study, the Gaussian kernel is considered, thereby only the bandwidth parameter $h$ should be defined.

The MSC algorithm automatically determines the number of data clusters relying on the bandwidth, which dictates the size of the region to search through. These clusters are automatically correlated to the number of discovered modes. The nonparametric characteristic of MSC makes it a powerful tool to discover arbitrarily shaped clusters present in the monitoring data from SHM applications, aiming to establish the baseline or normal condition of the monitored structure.

### 2.2 Damage detection using discovered clusters

After the definition of the optimal number of data clusters embedded in the training data, the damage detection process is performed through a global damage indicator (DI) estimated for each test observation. Basically, for a given test feature vector, $z_i$ ($i = 1, \ldots, l$), the ED for all centroids is calculated, where the DI($i$) is considered the smallest distance,

$$DI(i) = \min \left( \| z_i - c_1 \|, \| z_i - c_2 \|, \ldots, \| z_i - c_Q \| \right),$$

(6)

where $c_1, c_2, \ldots, c_Q$ are the centroids of $Q$ different data clusters. In this study, the threshold for damage classification is defined for 95% of confidence on the DIs taking into account only the baseline data used in the training process. Thus, if the MSC approach has learned the baseline condition, i.e., the identified data clusters suitably represent the undamaged and normal condition under all possible operational and environmental conditions, then this approach should output approximately 5% of false alarms for the undamaged data used in test phase.
3. TEST STRUCTURE AND DATA SETS

The Z-24 Bridge was a post-tensioned concrete box girder bridge composed of a main span of 30 m and two side-spans of 14 m, as depicted in Figure 1. The bridge, before complete demolition, was extensively instrumented and tested with the purpose of providing a feasibility benchmark for vibration-based SHM in civil engineering [19]. A long-term monitoring test was carried out, from 11 November 1997 until 10 September 1998, to quantify the operational and environmental variability present on the bridge and detect damage artificially introduced, in a controlled manner, in the last month of operation. Every hour, eight accelerometers captured the vibrations of the bridge as sequences of 65536 samples (sampling frequency of 100 Hz) and other sensors measured environmental parameters, such as temperature at several locations [20].

Figure 1: Longitudinal section (left), and the location and orientation of accelerometers (right) on the Z-24 Bridge. Marked sensors failed during the monitoring campaign.

In this case, the natural frequencies of the Z-24 Bridge are used as damage-sensitive features. They were estimated using a reference-based stochastic subspace identification method on vibration measurements from the accelerometers [21]. The first two natural frequencies estimated daily from 11 November 1997 to 10 September 1998, with a total of 235 observations, are highlighted in Figure 2. The first 198 observations correspond to the damage-sensitive feature vectors extracted within the undamaged structural condition under effects caused by the operational and environmental variability. The last 37 observations correspond to the damage progressive testing period, which is highlighted, especially in the second frequency, by a clear decay in the magnitude of such frequency. The damage scenarios were carried out in a sequential manner, which cause cumulative degradation of the bridge. Moreover, the observed jumps in the natural frequencies are related to the asphalt layer in cold periods, which significantly contributes to the stiffness of the bridge.

Progressive damage tests were performed in one-month time period (from 4 August to 10 September 1998) before the demolition of the bridge to prove that realistic damage has a measurable influence on the bridge dynamics, as summarized in Table 1. The continuous monitoring system was still running
during the progressive damage tests, which permits one to validate the SHM system to detect accumul-

ative damage on long-term monitoring.

<table>
<thead>
<tr>
<th>Date</th>
<th>Scenario description</th>
<th>Date</th>
<th>Scenario description</th>
</tr>
</thead>
<tbody>
<tr>
<td>04-08-98</td>
<td>Undamaged condition</td>
<td>25-08-98</td>
<td>Spalling of concrete at soffit (12 m²)</td>
</tr>
<tr>
<td>09-08-98</td>
<td>Installation of the PSS</td>
<td>26-08-98</td>
<td>Spalling of concrete at soffit (24 m²)</td>
</tr>
<tr>
<td>10-08-98</td>
<td>Lowering of pier, 2 cm</td>
<td>27-08-98</td>
<td>Landslide of 1 m at abutment</td>
</tr>
<tr>
<td>12-08-98</td>
<td>Lowering of pier, 4 cm</td>
<td>31-08-98</td>
<td>Failure of concrete hinge</td>
</tr>
<tr>
<td>17-08-98</td>
<td>Lowering of pier, 8 cm</td>
<td>02-09-98</td>
<td>Failure of 2 anchor heads</td>
</tr>
<tr>
<td>18-08-98</td>
<td>Lowering of pier, 9.5 cm</td>
<td>03-09-98</td>
<td>Failure of 4 anchor heads</td>
</tr>
<tr>
<td>19-08-98</td>
<td>Lifting of pier, tilt of foundation</td>
<td>07-09-98</td>
<td>Rupture of 2 out of 16 tendons</td>
</tr>
<tr>
<td>20-08-98</td>
<td>New reference condition (after removal of the PSS)</td>
<td>08-09-98</td>
<td>Rupture of 4 out of 16 tendons</td>
</tr>
<tr>
<td></td>
<td></td>
<td>09-09-98</td>
<td>Rupture of 6 out of 16 tendons</td>
</tr>
</tbody>
</table>

In conclusion, the damage detection process will be carried out by taking into account the first two natural frequencies and using all 235 observations, resulting in 198 observations from the undamaged condition (1–198 observations) and 37 observations from the damaged condition (199–235 observations). The corresponding training and test matrices are $X^{198 \times 2}$ and $Z^{235 \times 2}$, respectively. The multimodality and heterogeneity among observations in a two dimensional space suggests the existence of data groups that may be find through cluster-based methods.

4. RESULTS AND DISCUSSION

In this section the performances of the K-means-, FCM-, GMM-, and MSC-based approaches are com-
pared in terms of a reliable estimation of data clusters for the undamaged condition and all conditions
(undamaged and damaged conditions), and Type I/Type II errors to evaluate the damage classification
performance. For K-means and FCM, the Calinski-Harabasz criterion [22] was used to off-line infer the
number of clusters. The bandwidth parameter $h$ for the MSC was selected based on the best compromise
between the bias and variance [17]. The GMM was set as described in [7], where the model parameters
are estimated from the data using the expectation-maximization (EM) algorithm.

4.1 Estimation of data clusters for the undamaged condition

The clustering performance of all approaches for baseline condition is shown in Figure 3. K-means,
FCM, and GMM have approximately the same cluster configuration, with two data clusters, where the
black one is possibly related to the baseline condition obtained under relatively small environmental
and operational influences; and the blue one may be assigned to the baseline condition under severe
temperature variations, which corresponds to changes in the structural stiffness [20]. On the other hand,
the MSC with $h = 0.147$ presents three data clusters, where the black one is, again, possibly related to
the undamaged condition obtained under minor environmental and operational factors; the blue and cyan
ones are related to gradual decrease of temperature in the asphalt layer (enough to slightly change the
elastic properties of the structure) and changes in the structural response derived from stiffness variations
in the asphalt layer caused by freezing temperatures, respectively.

Comparing the results from the MSC and state-of-the-art algorithms, one may verify the similarity
of the clustering results for the first data cluster. However, the state-of-the-art algorithms agglutinate
the second and third clusters suggested by the MSC algorithm, incorporating all gradual changes in
the asphalt layer to one cluster only. Therefore, the proposed approach can discriminate the normal
and stable state conditions of the Z-24 Bridge in a better manner, separating changes caused by regular
temperatures from changes caused by extreme cold temperatures.
4.2 Estimation of data clusters for all conditions

The clustering performance of all approaches for undamaged and damaged conditions is highlighted in Figure 4. In this case, K-means and FCM have approximately the same cluster configuration, with three data clusters, where the red one is related to the damage progressive test period, integrating all damaged scenarios into one cluster only and presenting 1 or 2 mislabels for all conditions. As the worst case, GMM seems to define data clusters without a logic distinction between undamaged and damaged conditions, outputting several mislabels for all conditions. On the other hand, the MSC with $h = 0.126$ presents five data clusters, where the damage progressive test period is better specified in a logic manner. The second damaged cluster (in magenta) is related to the first few damaged scenarios that consist of installing a settlement system in one pier and then simulating pier settlements of increasing magnitude, followed by a simulated foundation tilt. After these scenarios, on the 20 August 1998, the pier was brought back to its initial position, causing cracks in the bridge deck. The first damaged cluster (in red) is related to the additional damage introduced incrementally, from 25 August 1998, resulting in a pronounced increase in the accumulated damage level in long-term monitoring.

When the results from the MSC and state-of-the-art algorithms are compared, one may infer the advantage of the cluster configuration provided by MSC as it can capture and distinguish different damage levels, ignored by other approaches, which illustrates that the output-only monitoring strategy proposed in this study is a powerful method for SHM.
Figure 4: Clustering performance of the approaches on the test data: K-means (upper left), FCM (upper right), GMM (lower left), and MSC (lower right).

4.3 Damage detection performance

The DIs obtained from the test matrix, \( Z^{235 \times 2} \), along with a threshold defined based on the 95% cut-off value over the training data, are depicted in Figure 5. It shows that the K-means-, FCM- and MSC-based approaches outputs a monotonic relationship between the level of damage and the amplitude of the DIs, which may be attributed to the reliable estimation of data clusters provided by these methods during the training phase; whereas the GMM fails to establish this relationship, which may be assigned to an inappropriate definition of data clusters during training phase due to the stochastic behavior of the EM algorithm that compromises the estimation of posterior probability that the observation came from the corresponding cluster. Besides, when one look at the range of baseline condition, the patterns in the DIs caused by the freezing effects can not be pointed out for the MSC, which indicates that this approach is able to remove almost all effects of environmental variations and so demonstrates to be effective to model the normal condition.

Therefore, to quantify the damage classification performance for the test matrix, Table 2 synthesizes the Type I and Type II errors for all approaches. Basically, the GMM- and MSC-based approaches have the same classification performance, reaching 5.05% of Type I errors (as expected) and no misclassification of Type II errors, respectively, and a total amount of errors equal to 4.26%. These results are quite similar due to the damage detection based on ED adopted to identify outliers. However, the MSC filters nearly all operational and environmental variability, especially in the damaged observations, instead of the GMM that provides a poor data normalization in these observations. As expected, the K-means an FCM-based approaches obtained similar results in relation to the amount of Type I errors; however, the Type II errors reached over 2.7%, demonstrating some inefficiency when classifying abnormal conditions.
Figure 5: Outlier detection for each approach: K-means (upper left), FCM (upper right), GMM (lower left), and MSC (lower right).

<table>
<thead>
<tr>
<th>Approach Type</th>
<th>Type I errors</th>
<th>Type II errors</th>
<th>Total errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-means</td>
<td>10 (5.05%)</td>
<td>1 (2.70%)</td>
<td>11 (4.68%)</td>
</tr>
<tr>
<td>FCM</td>
<td>10 (5.05%)</td>
<td>1 (2.70%)</td>
<td>11 (4.68%)</td>
</tr>
<tr>
<td>GMM</td>
<td>10 (5.05%)</td>
<td>0 (0.00%)</td>
<td>10 (4.26%)</td>
</tr>
<tr>
<td>MSC</td>
<td>10 (5.05%)</td>
<td>0 (0.00%)</td>
<td>10 (4.26%)</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

In this paper was presented the MSC approach that automatically discovers data clusters in a smooth density of observations by updating candidate centroids to be the mean of the observations (highest density region) within a given region defined by the bandwidth of a Gaussian kernel. After the main state conditions of the structure are determined, assuming no underlying distributions, the damage detection strategy based on ED is applied. The damage classification performance of the MSC on challenging vibration-based data sets was evaluated and compared to state-of-the-art methods.

The classification performance for the real-world SHM scenario, Z-24 Bridge, attested that the MSC approach is better than the alternative ones presented in this study. When the MSC is compared to the GMM, the instability and unreliability of the EM algorithm demonstrated to have a direct and negative impact on the identification of reliable data clusters (data normalization), which affected the
relationship between the level of damage and the amplitude of the DIs in the damage detection phase; whereas the MSC discovers well-defined clusters, improving the data normalization and damage detection processes. The K-means and FCM appear to be less affected than the GMM by the choice of the initial parameters, nevertheless they are dependent on the choice of the number of clusters in advance. Such drawback may influence their competence to remove almost all undesired operational and environmental variations and, consequently, resulted in worst classification performance regarding Type II errors.

In contrast to the other approaches, the MSC is a nonparametric technique that does not require prior knowledge of the number of data clusters and can identify clusters of distinct shapes, sizes and density. Unfortunately, the MSC is not highly scalable, as it requires multiple nearest neighbor searches during the execution of the algorithm. This disadvantage is circumvented through parallel implementation of the MSC. As demonstrated through the experimental results, this cluster-based approach proved to be a pronounced technique that can be used in SHM applications where life-safety, economic and reliability issues must be considered as primary motivations.

REFERENCES


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