Applicability of a Markov-Chain Monte Carlo Method for Damage Detection on Data from the Z-24 and Tamar Suspension Bridges

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ABSTRACT

In the Structural Health Monitoring of bridges, the effects of the operational and environmental variability on the structural responses have posed several challenges for early damage detection. In order to overcome those challenges, in the last decade recourse has been made to the statistical pattern recognition paradigm based on vibration data from long-term monitoring. The use of purely data-based algorithms that do not depend on the physical descriptions of the structures have characterized this paradigm. However, one drawback of this procedure is how to set up the baseline condition for new and existing bridges. Therefore, this paper proposes an algorithm with a Bayesian approach based on a Markov-chain Monte Carlo method to cluster structural responses of the bridges into a reduced number of global state conditions, by taking into account eventual multimodality and heterogeneity of the data distribution. This approach, along with the Mahalanobis squared-distance, permits one to form an algorithm able to detect structural damage based on daily response data even under abnormal events caused by operational and environmental variability. The applicability of this approach is first demonstrated on standard data sets from the Z-24 Bridge, Switzerland. Afterwards, for generalization purposes, it is applied on datasets from a supposed undamaged bridge condition, namely the Tamar Bridge, England. The analysis suggests that this algorithm might be useful for bridge applications, because it permits one to overcome some of the limitations posed by the pattern recognition paradigm, especially when dealing with limited amounts of training data.

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INTRODUCTION

The process of implementing a damage detection strategy for existing structures is referred to as Structural Health Monitoring (SHM). Under that definition, damage is normally defined as changes to the material and/or geometric properties of the structural systems, including changes to the boundary conditions and system connectivity, which adversely affect the system's current or future performance. The authors pose the SHM process in the context of a statistical pattern recognition (SPR) paradigm [1]. In this paradigm, the process can be broken down into four steps: (1) operational evaluation, (2) data acquisition, (3) feature extraction, and (4) statistical model development for feature classification. This paper addresses the fourth step of the SPR paradigm by presenting an algorithm for damage detection, with a Bayesian approach based on a Markov-chain Monte Carlo method, under varying and unknown conditions. Those conditions might be associated with operational and environmental variability generally present in the structures. This approach is of the most importance when one wants to implement a real-time damage detection strategy on data from real-world bridges.

The Bayesian approach carries out a model-based clustering, using multivariate finite mixture models, which aims to capture the main clusters/components of features that correspond to the normal and stable state conditions of a bridge, even when it is affected by extreme operational and environmental conditions. After that, instead of using a static Bayesian inference for outlier detection, a simpler dynamical approach is proposed, which permits one to track the outlier formation in time in relation to the chosen main groups of states. The damage detection is carried out on the basis of an outlier detection strategy using a machine learning method based on the Mahalanobis Squared-Distance (MSD).

For generality purposes, the damage detection algorithm is tested in the context of structural changes caused by varying operational and environmental conditions, which can mask the effects caused by damage. Actually, the authors believe that the separation of the changes in the structural responses caused by operational and environmental variability, from the changes caused by damage, is one of the biggest challenges to transit SHM technology from research to practice [2]. The challenges posed by the effects of the operational and environmental variability, on the damage detection process, have been extensively pointed out by several studies. For instance, Farrar et al. [3] performed vibration tests on the I-40 Bridge over the Rio Grande in New Mexico, USA, in order to investigate if modal parameters could be used to identify damage to the structure. Cuts in four increasing level stages were made in a mid-span plate girder to simulate the formation of fatigue cracks. For the fundamental natural frequency, it was observed that the magnitude increased for the first two levels of damage and decreased for the other two levels. Later investigation concluded that the ambient temperature of the bridge played a major role in the variation of the bridge's dynamic characteristics. Kim et al. [4] reported that the measured natural frequencies of a 46 m long simply-supported plate girder decreased by 5.4% as a result of heavy traffic.

The applicability of the proposed algorithm is demonstrated on standard data sets from both the Z-24 Bridge [7], in Switzerland, and the Tamar Suspension Bridge, England. The data sets from the Z-24 Bridge are unique in the sense that they combine one-year monitoring with realistic damage scenarios and effects of the operational and environmental variability. Actually, in 2001, Peeters et al. [8] performed a study on the Z-24 Bridge data addressing the influence of the temperature effect on the modal parameters. The authors speculated that differences in the natural frequencies ranging from 14-18% must be explained by environmental changes. On the other hand, the Tamar Bridge is unique in the sense that it combines data sets from a large period of observation when the structure is thought to be undamaged. Actually, analyses on data from the Tamar Bridge have shown that the total mass of traffic is the most influential parameter on the bridge's dynamic performance, followed by the temperature. The authors claimed that temperature and traffic impose fluctuations, in the first lateral frequency, by around 10% [5,6].

Note that even though several environmental factors, such as temperature and humidity, were measured during the period of observation, the approach presented herein does not take them into account for the damage detection process. Therefore, the damage-sensitive features are only based on vibration response data from the bridge.

DAMAGE DETECTION ALGORITHM WITH A BAYESIAN APPROACH BASED ON MARKOV-CHAIN MONTE CARLO

Suppose that a data set $\mathbf{Y} = (\mathbf{y}_1,...,\mathbf{y}_T)$ is available, which consists of T i.i.d. observations of a random variable/vector, arising from a mixture of K distributions,

$$f_{mix}(\mathbf{y}_i) = \sum_{k=1}^{K} \eta_k f_k(\mathbf{y}_i \mid \theta_k), \tag{1}$$

with $f_k(\mathbf{y}_i \mid \theta_k)$ being the density of a distribution from a known parametric distribution family $\tau(\theta)$.

In this setting, one is concerned with the estimation of the component parameters $\theta = (\theta_1,...,\theta_K)$ and the weight distribution $\eta = (\eta_1,...,\eta_K)$ of the underlying mixture distributions, based on the data $\mathbf{Y}$. Herein, the purpose is to employ a Bayesian approach based on a MCMC algorithm as described in Fruhwirth-Schnatter [9], as an alternative to the classical maximum likelihood (ML) estimation based on the expectation-maximization (EM) algorithm. The main difference of the Bayesian approach, from the ML approach, is the inclusion of a proper prior distribution on the component parameter, which has a smoothing effect on the mixture likelihood function and reduces the risk of obtaining spurious modes in cases where the EM algorithm leads to degenerate solutions.

The Bayesian approach is composed of a two-step iterative procedure based on the complete-data likelihood function $p(\mathbf{Y},\mathbf{S} \mid \theta,\eta)$ given by

$$\log p(\mathbf{Y},\mathbf{S} \mid \theta,\eta) = \sum_{i=1}^{T} \sum_{k=1}^{K} \delta_{ik} \log(\eta_k f_k(\mathbf{y}_i \mid \theta_k)), \tag{2}$$

where $\mathbf{S} = (S_1,...,S_T)$ are considered to be allocations of each observation to its corresponding component in the mixture and δ_{ik} is a 0/1 coding of this allocation, $S_i : \delta_{ik} = 1$, if and only if $S_i = k$ (i.e. if the observable $\mathbf{y}_i$ comes from component k of the mixture). The allocations $\mathbf{S} = (S_1,...,S_T)$ are regarded as data without a value stored in the current observation, i.e. missing data or (unobserved) latent variables.

The Bayesian approach to a mixture model, estimates the augmented parameter set $(\mathbf{S},\theta,\eta)$ by sampling from the complete-data posterior distribution $p(\mathbf{S},\theta,\eta\,|\,\mathbf{Y})$. In this setting, the posterior distribution is given by Bayes' theorem

$$p(\mathbf{S},\theta,\eta\,|\,\mathbf{Y}) \propto p(\mathbf{Y}\,|\,\mathbf{S},\theta,\eta)\,p(\mathbf{S}\,|\,\theta,\eta)\,p(\theta,\eta) \propto p(\mathbf{Y},\mathbf{S}\,|\,\theta,\eta)\,p(\theta,\eta). \tag{3}$$

DESCRIPTION OF THE Z-24 AND THE TAMAR SUSPENSION BRIDGES

The Z-24 Bridge was a standard post-tensioned concrete box girder bridge composed of a main span of 30m and two side-spans of 14m (Figure 1). The bridge, before complete demolition, was extensively instrumented and tested with the aim of providing a "feasibility tool" for vibration-based SHM in civil engineering. 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 to detect the existence of damage artificially introduced, approximately, in the last month of the observation period (4th of August to 10th of September 1998). Every hour, environmental quantities, such as temperature at several locations, were measured from an array of sensors. In particular, every hour, eight accelerometers captured the vibrations of the bridge for 11 minutes. Progressive damage tests (settlement, concrete spalling, landslide at abutment, concrete hinge failure, anchor head failure, and rupture of tendons) were carried out in a one-month time period shortly before the demolition of the bridge, in order to prove that realistic damage has a measurable influence on the bridge dynamics [7]. Note that the continuous monitoring system was still running during the progressive damage tests, which permits one to validate the SHM system to detect accumulative damage on long-term monitoring.

The Tamar Suspension Bridge (Figure 1) carries the A38 trunk road from Saltash in Cornwall to the city of Plymouth in Devon within the United Kingdom. Since 1961 the bridge structure was a steel truss supported vertically by a pair of suspension cables. In order to meet a European Union Directive that bridges should be capable of carrying lorries of up to 40 tonnes, the bridge underwent a strengthening and widening upgrade scheme, which was completed in 2001. The upgrade consisted of adding cantilevered lanes either side of the truss to provide a total of four lanes for traffic and a footpath for pedestrians. The heavy composite deck was replaced by an orthotropic steel deck and eight pairs of stay cables connected to the towers were added to support the increased weight of the deck.

In order to track the effects of the upgrade, a monitoring system was installed by FUGRO to determine the performance of the structure, as well as to record environmental effects such as wind speeds and ambient and structural temperatures. Five years later a dynamic response monitoring system with real time modal parameter identification was installed. This system includes three accelerometers located at the centre of the main span that record vertical and sway vibrations of the deck structure. The data from both the FUGRO and dynamic monitoring systems are summarized into 30-minute intervals, so that data collected over several years can be compared to determine possible environmental and operational influences on the bridge's performance.

Figure 1. The Z-24 Bridge (left) and Tamar Suspension Bridge (right).

DATA ANALYSIS: APPLICABILITY OF THE ALGORITHM

For the Z-24 Bridge, the applicability of the approach was explored using daily natural frequencies estimated from acceleration time series measured at 5am, due to the low levels of traffic and to minimize the temperature differential. Figure 2 plots those frequencies (235 observations). The last 38 observations correspond to the damage progressive testing period, which is highlighted, especially in the second frequency, by a clear drop in the frequency's magnitude. Note that the damage scenarios are carried out in a sequential manner, which cause a cumulative degradation of the bridge. Therefore, in this study, it is assumed that the bridge operates within its undamaged condition (baseline condition) from 11th of November 1997 to 3rd of August 1998 (observations 1-197) under operational and environmental variability. The observed jumps in the natural frequencies are related to the asphalt layer, in cold periods, that contributes significantly to the stiffness of the bridge [8]. On the other hand, the bridge is assumed in its damaged condition from 4th of August to 10th of September 1998 (observations 198-235).

Figure 3 plots, the MSD of each observation (1-197) to the empirical mean against the corresponding percentile of the Chi-Square distribution with two degrees of freedom, χ_2^2. As the points do not lie on a straight line, it is assumed that the entire data set does not follow a single bivariate normal distribution. Therefore, this fact suggests the use of other models that eventually will allow one to use the Gaussian assumption. One method to achieve that is to model the baseline condition of the data using only the main normal components. Figure 4 plots a finite mixture of bivariate normal distributions to the baseline data. The number of components, weights, and mean vectors are summarized in Table 1. The main component accounts for 81% of the baseline data, which corresponds to the undamaged condition without major effects caused by operational and environmental variability. The second component accounts for 19% of the baseline data, which takes into account the extreme effects of the operational and environmental conditions, including the ones caused by freezing temperature in the asphalt layer.

After the above unsupervised learning stage to infer the heterogeneity of the data under varying operational and environmental conditions, the next step is to lay out a procedure to incorporate prior knowledge of the baseline data into the damage detection process. Two independent MSD models, based on the two main components from the baseline condition, are set to match the two components of the model. Figure 5 plots daily Damage Indexes (DI), where each DI corresponds to the minimum MSD coefficient of those two MSD models, along with a threshold defined for the 95% confidence region of that component. In this case, it is possible to verify the performance of the classifier because of the existence of known damaged structural responses. Thus, the Error Type I (false-positive indication of damage) and the Error Type II (false-negative indication of damage) is a common method of reporting the performance of a binary classification. This technique recognizes that a false-positive classification may have different consequences than a false-negative one. In this case, one can highlight four Error Type I and two Error Type II, which seems to be a reasonable classification performance based on the level of significance used (α=5%).

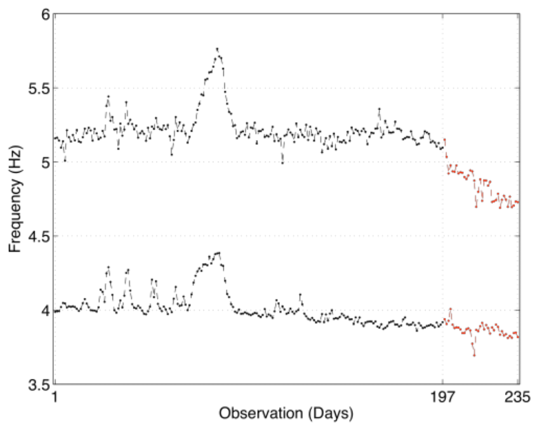

Figure 2. First two natural frequencies estimated at 5am.

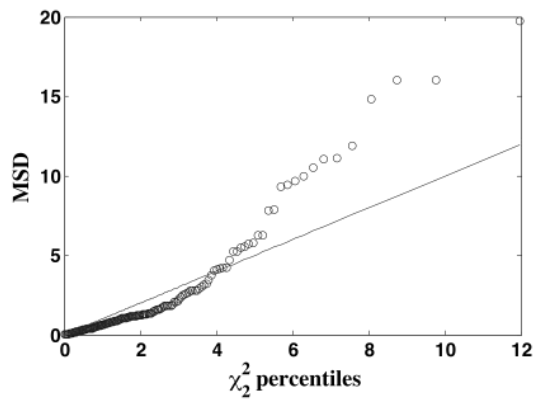

Figure 3. Chi-square plot to verify the multimodality of the observations.

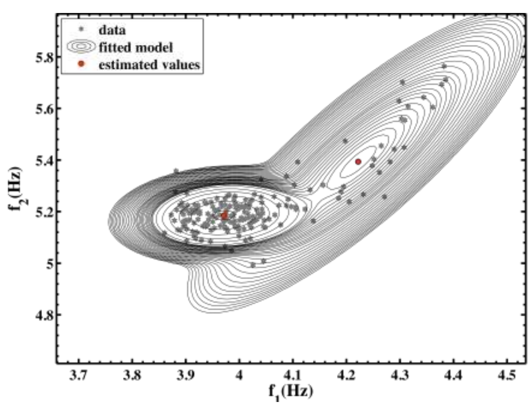

Figure 4. Fitted bivariate normal mixture distribution with K=2 on the undamaged data set.

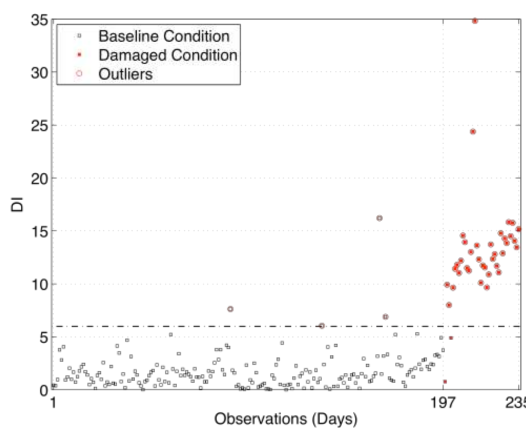

Figure 5. Daily DIs along with threshold defined for the 95% confidence region of the two components.

Table 1. Components (k=2) of the observations from the baseline condition given by the marginal likelihood.

Description		Components	
		#1	#2
Weight (%)		81	19
Mean (Hz)	f_1	3.97	4.22
	f_2	5.19	5.39

In the case of Tamar Suspension Bridge, and following the same procedure used for the Z-24 Bridge, Figure 6 shows a plot of the first five natural frequencies estimated at 5am from 1st of July 2007 to 24th of February 2009 (602 observations). As the real structural condition of the bridge is not known a priori, 50% of the observations were used to find the number of normal components (observations 1-301, from the beginning until 29th of April 2008). In this case, and as suggested in Figure 7, the MSD of each observation to the empirical mean against the corresponding percentile of the Chi-Square distribution, χ_5^2, suggests that the data follow a multivariate normal distribution reasonably well. The number of components K=4 (given by the marginal likelihood), weights, and mean vectors are summarized in Table 2. The results suggest that the means of each component are relatively close, which confirm the indications of Figure 7 regarding the existence of a multivariate normal distribution. Those indications are further confirmed in Figure 8, which plots 50% of the bi-dimensional data given by the first and fourth natural frequencies along with the finite mixture model of multivariate normal distributions. In terms of a structural point of view, the multi-normal distribution indicates that the structure changes very little in time and probably shifts between four unknown operational and environmental conditions. Nevertheless, Figure 9 plots daily DIs, where each DI corresponds to the minimum MSD coefficient of those four MSD models, along with a threshold defined for the 95% confidence region.

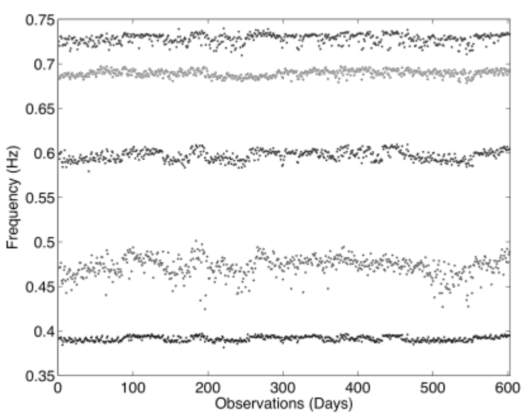

Figure 6. First five natural frequencies estimated at 5am from 01/07/2007 to 24/02/2009.

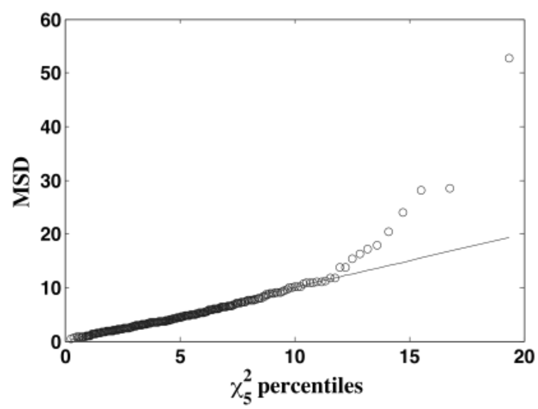

Figure 7. Chi-square plot to verify the multimodality of the observations.

Table 2. Components (k=4) of the observations from 50% of the data given by the marginal likelihood.

Description		Component			
		#1	#2	#3	#4
Weight (%)		29	33	24	15
Mean (Hz)	f_1	0.39	0.39	0.39	0.39
	f_2	0.47	0.48	0.47	0.47
	f_3	0.59	0.60	0.59	0.60
	f_4	0.69	0.69	0.69	0.69
	f_5	0.72	0.73	0.73	0.72

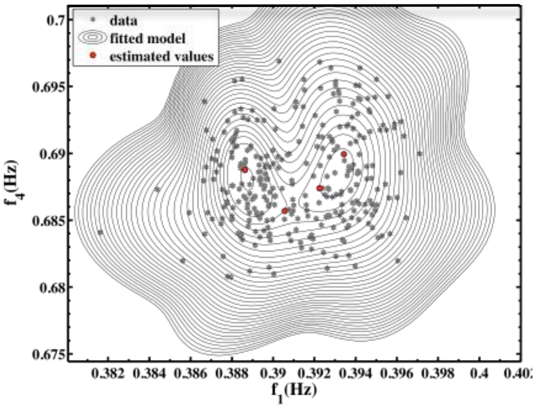

Figure 8. Fitted normal mixture distribution with K=4 on 50% of the data set.

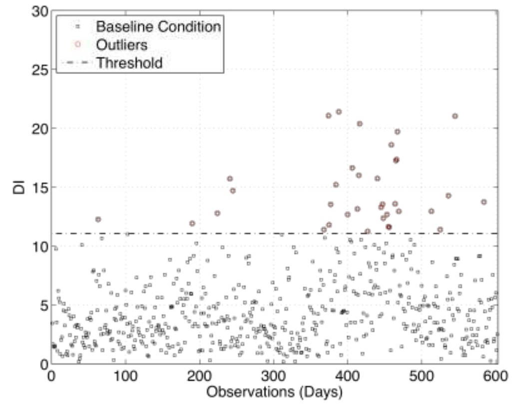

Figure 9. Daily DIs along with threshold for the 95% confidence region of the four components.

CONCLUSIONS

This parametric approach has several advantages over other non-parametric approaches because: (i) it permits the generalization of the underlying distribution of the observations, which might be useful in those cases where there is not enough data to fully characterize their density distribution; and (ii) the assumption of parametric distributions permits one to define thresholds for certain level of significance, which might be useful for real-world applications.

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