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Guaranteeing robustness of structural condition monitoring to environmental variability

Kendra Van Buren [a], Jack Reilly [b], Kyle Neal [c], Harry Edwards [d], François Hemez [e,*]

[a] Los Alamos National Laboratory, XCP-8, Mail Stop F644, Los Alamos, NM 87545, USA
[b] Princeton University, Department of Civil and Environmental Engineering, Princeton, NJ 08544, USA
[c] Vanderbilt University, Department of Civil and Environmental Engineering, Box 1831-B, Nashville, TN 37235, USA
[d] Atomic Weapons Establishment, Environment and Test Group, Reading, United Kingdom
[e] Los Alamos National Laboratory, XTD-IDA, Mail Stop T087, Los Alamos, NM 87545, USA

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ABSTRACT

Advances in sensor deployment and computational modeling have allowed significant strides to be recently made in the field of Structural Health Monitoring (SHM). One widely used SHM strategy is to perform a vibration analysis where a model of the structure's pristine (undamaged) condition is compared with vibration response data collected from the physical structure. Discrepancies between model predictions and monitoring data can be interpreted as structural damage. Unfortunately, multiple sources of uncertainty must also be considered in the analysis, including environmental variability, unknown model functional forms, and unknown values of model parameters. Not accounting for these sources of uncertainty can lead to false-positives or false-negatives in the structural condition assessment. To manage the uncertainty, we propose a robust SHM methodology that combines three technologies. A time series algorithm is trained using "baseline" data to predict the vibration response, compare predictions to actual measurements collected on a potentially damaged structure, and calculate a user-defined damage indicator. The second technology handles the uncertainty present in the problem. An analysis of robustness is performed to propagate this uncertainty through the time series algorithm and obtain the corresponding bounds of variation of the damage indicator. The uncertainty description and robustness analysis are both inspired by the theory of info-gap decision-making. Lastly, an appropriate "size" of the uncertainty space is determined through physical experiments performed in laboratory conditions. Our hypothesis is that examining how the uncertainty space changes throughout time might lead to superior diagnostics of structural damage as compared to only monitoring the damage indicator. This methodology is applied to a portal frame structure to assess if the strategy holds promise for robust SHM. *(Publication approved for unlimited, public release on October-28-2015, LA-UR-15-28442, unclassified.)*

* Corresponding author.
E-mail addresses: klvan@lanl.gov (K. Van Buren), jpr2@princeton.edu (J. Reilly), kyle.d.neal@vanderbilt.edu (K. Neal), Harry.Edwards@awe.co.uk (H. Edwards), hemez@lanl.gov (F. Hemez).

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1. Introduction

In the discipline of Structural Health Monitoring (SHM), the condition of a structure is often assessed using a combination of physical measurements and predictions from mathematical or numerical models [1,2]. The paradigm is to infer the structural condition from changes in the vibration response [3–6]. A structure inevitably degrades as it ages, through cycles of thermal loading, structural loading, and other conditions that affect structural health. As a result of this structural degradation, at some point, the structure may no longer be able to meet its performance requirements. This work contributes to the vast body of literature that develops diagnostics to detect such changes before they become safety or mission critical [7,8].

To detect the onset of changes that could adversely affect structural integrity, the state-of-the-practice is to attach sensors to the structure and measure its vibration response from external excitation. Commonly, accelerometers and strain gauges are used to measure the structure's response [9,10]. For in-service structures, ambient excitations such as cars on a bridge, wind over a building, or ground vibrations are typically used to elicit the vibration response [11,12]. In contrast, it is common to perform deliberate and controlled excitation such as a modal hammer impact strike or modal shaker for laboratory tests. Diagnostics of structural health can be sought by analyzing changes to the Frequency Response Function (FRF) data, which is appropriate for dynamics that remain mostly linear and stationary [13,14]. Another approach is to train a time series model on the pristine condition of the structure, and then use the model to predict the structure's response and assess if its condition remains unchanged [15–17]. Shifts in natural frequencies observed from the FRF data, or deviations from predictions of time series models, could indicate structural damage [14,18]. It is emphasized that this process is only effective if measurements of the structure in its current state can be compared to measurements obtained from the pristine structure, which form a known “baseline.” In the absence of baseline test data, mathematical modeling can be substituted to create theoretical “data” of the pristine state [19].

In this study, a time series model from the family of Auto Regressive (AR) representations [20] is used to analyze the acceleration response data (measurements) from an aluminum frame structure tested in controlled laboratory settings. The AR model is trained using multiple sets of vibration responses collected while the structure is in a “pristine,” or undamaged, condition. The hypothesis is that the occurrence of damage manifests itself as a significant difference between what is measured on the (now damaged) structure and what the trained AR model predicts. The difference in structural condition, from undamaged to damaged, is diagnosed by large prediction residuals. A damage indicator is proposed that derives from statistics of the prediction residuals.

While the aforementioned strategy is well accepted within the SHM community, one challenge, which remains for the most part unresolved, is the quantification of uncertainty. A change in vibration signature does not necessarily indicate that the structure is damaged. It might, instead, be due to environmental variability, such as a change in temperature or input excitation [21]. To avoid the possibility of generating false-positives or false-negatives, it is highly desirable to “separate” the effects of environmental variability from those of structural damage.

Another unavoidable source of uncertainty is lack-of-knowledge associated to the model used to predict the vibration response. For example, when using the AR representation, the choice of model order has been shown to affect the assessment of structural health [20]. Further, when training a model of arbitrary mathematical form, its parameters might be non-unique whereby multiple sets of parameter values are able to replicate the training data with comparable fidelity. It is highly desirable to “separate” the effects of model-form uncertainty from those of structural damage. In this work, the effects of environmental uncertainty are quantified by replicating the vibration tests when the input excitation signal is varied within reasonable bounds. Likewise, the effects of modeling uncertainty are quantified by analyzing, not a single best-fitted time series model, but a family of models that includes all representations that fit the measurements with a similar level of accuracy. The effects of these two main sources of uncertainty (environmental variability and model-form uncertainty) are quantified such that the structural damage detection can be rendered ***robust*** to their unavoidable occurrence [22].

The description of environmental variability and modeling lack-of-knowledge is inspired by the theory of information-gap (or info-gap) for decision-making [23]. The magnitude, or “size,” of the uncertainty, which the decision (*“is the structural state pristine or damaged?”*) must be robust to, is controlled by a horizon-of-uncertainty parameter denoted by α. A larger value of α increases the uncertainty considered in the analysis and, therefore, allows for greater potential deviation between reality and the numerical model used to predict the structural state. Refs. [24,25] provide examples of defining the horizon-of-uncertainty α, and performing an analysis of robustness, for applications to groundwater flow and transient dynamics, respectively.

This research aims to assess structural conditions in a manner that is immune (robust) to uncertainty. To do so, two concepts are combined. Firstly, the maximum horizon-of-uncertainty, α, required to capture the environmental variability and modeling lack-of-knowledge for the pristine state is determined. This is a conventional analysis of robustness such as proposed, for instance, in Refs. [22,23]. Secondly, damage is diagnosed by observing whether α increases, which would indicate “growth” of the uncertainty space, as the (potentially damaged) structure progressively deviates from the pristine state. The novelty is to assess how α changes over time, after having set a “baseline” that represents the environmental variability. While embedding an info-gap model of uncertainty within damage detection has been previously achieved (see, for example, an application to neural networks in Ref. [26]), monitoring the growth of the uncertainty space is an aspect unique to this work. Another enhancement is the ability to account for the correlation structure of our uncertainty