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Modeling and diagnosis of structural systems through sparse dynamic graphical models

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ABSTRACT

Since their introduction into the structural health monitoring field, time-domain statistical models have been applied with considerable success. Current approaches still have several flaws, however, as they typically ignore the structure of the system, using individual sensor data for modeling and diagnosis. This paper introduces a Bayesian framework containing much of the previous work with autoregressive models as a special case. In addition, the framework allows for natural inclusion of structural knowledge through the form of prior distributions on the model parameters. Acknowledging the need for computational efficiency, we extend the framework through the use of decomposable graphical models, exploiting sparsity in the system to give models that are simple to fit and understand. This sparsity can be specified from knowledge of the system, from the data itself, or through a combination of the two. Using both simulated and real data, we demonstrate the capability of the model to capture the dynamics of the system and to provide clear indications of structural change and damage. We also demonstrate how learning the sparsity in the system gives insight into the structure's physical properties.

1. Introduction

As the number and complexity of mechanical and structural systems increases, there grows a need for automated tools to diagnose damage and other anomalies. For instance, airlines may be interested in maximizing the lifespan and reliability of their jet engines, or governmental authorities might like to monitor the condition of bridges and other civil infrastructures in an effort to develop cost-effective lifecycle maintenance strategies. These examples indicate that the ability to efficiently and accurately monitor all types of structural systems is crucial for both economic and life-safety issues. This issue of detecting and explicating damage in engineering structures, known as structural health monitoring (SHM), is facing increasing challenges as existing approaches reach their limit due to growing streams of data from multifarious systems across diverse environmental conditions. Methods are needed, therefore, which tackle the torrent of data and diverse application environments in a manner which separates natural variability from variability caused by damage. This work attempts to address this problem by developing statistical methodologies to detect damage in the face of huge data sources

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across broad environmental variability. The proposed methods hold potential to improve economic and life-safety issues associated with all types of aerospace, civil and mechanical infrastructure through improved lifecycle management.

One important automated diagnosis technique is vibration-based damage detection, which operates under the premise that damage will manifest itself through a change in the structure's dynamic response [9,14]. This area of structural health monitoring (SHM) has received much attention, and several detailed reviews have been written [10,34]. These techniques generally fall into two categories – those that use physical process-based models to understand the structural system, and those that use statistical techniques to quantify the various sources of uncertainty present [13]. Both these two paradigms have been employed under a multitude of circumstances and frameworks. We propose to use statistical, in particular Bayesian, techniques to directly model the vibration data, while incorporating knowledge of the physical system through the use of prior distributions and specified sparsity in the statistical model.

This work builds off that of Fugate et al. [17] by modeling the vibration sensor output using autoregressive (AR) techniques. The linear response assumption inherent in AR models is usually justified, as most high-capital expenditure engineering systems are designed to respond in a linear manner to their postulated operational and environmental loading conditions when they are not damaged. Once a model is fit to the vibration data from the structure in its undamaged state, this model is then subsequently used to obtain an assessment of the model's fit to future data. The logic behind this approach is that damage or other structural anomalies will present themselves through changes in the vibration output that will result in a poor fit to the original model. There are many tools to assess the model's fit, the most common being the prediction residuals – the difference between the fitted model and the observed data. If these residuals are large and/or correlated, this indicates poor model fit, and hence structural anomalies. Under the proposed methodology, we can also use the marginal likelihood of the data to detect damage. Specifically, we can measure how likely the observed data is under the model, and conclude that there is damage if this likelihood becomes considerably small. To determine thresholds for determining damage, one can use a sequential probability ratio test [1], control charts [17] or alternative techniques [5].

Most approaches to date have built a single model for the output of each vibration sensor, using heuristic schemes to indicate damage [19]. More recently statistical tools have been used to combine prediction residuals from individual sensors in a statistically rigorous manner to allow for statistical testing and inference [5]. The proposed research makes significant gains by jointly modeling all sensor outputs in a multivariate autoregressive framework. The benefits of such an approach include more accurate modeling of the system, as the statistical model can borrow information from adjacent sensors to provide a more faithful representation of the structural dynamics. While most previous methods could only detect damage that manifested itself in any given sensor, our multivariate framework will also detect anomalies that appear through a change in the correlation structure of the system. One can imagine a situation, such as a crack or loosened bolt, where a system is damaged in such a way that the individual sensor outputs are only slightly affected, but the correlation in the system changes drastically. While previous methods are insensitive to such damage, our approach naturally handles damage that results in changes to the individual sensor outputs or the correlation between sensors. After damage has occurred, one can then use the estimated change in correlation to determine the location of the damage within the sensor network's spatial distribution. It is worth emphasizing that multivariate modeling has seen application in the structural health monitoring literature for some time [11,7,2,27,29,32]. However, the work presented herein extends significantly beyond these studies by adapting Bayesian autogressive models coupled with graphical models to the SHM problem. Graphical models have been used in sensor design and fusion, where the interest is in combining output from multiple sensors [28,30], but have not been applied to SHM. Also, non-Bayesian vector autoregressive methods have recently been proposed for damage detection [15,24,16], with the goal of building hypothesis tests for detecting signal novelty. These methods have ignored system structure, and as such do not naturally allow for the inclusion of physics-based knowledge of the system under study. Likewise for examining the correlation structure of the data from the sensor network; there is very little in the SHM literature on this approach. As such, the proposed multivariate techniques hold significant promise for improving the state-of-the-art in the SHM community.

The traditional AR approaches taken to date have also ignored structure in the system. A Bayesian approach is natural for including knowledge about the system, as there is always some system knowledge to inform the creation of a prior distribution, even if only weak knowledge. This knowledge can come from a variety of sources ranging from numerical models developed during the design process to previously acquired data from the structure when it is in a known condition. Knowledge of the system structure can also be used to introduce sparsity into the model parameters; for instance, if you know that two sensors will be uncorrelated, it is logical to set their correlation to zero instead of using valuable degrees of freedom to estimate it. This is especially important in the multivariate framework, which as a penalty for more accurate modeling capabilities has an increased number of parameters to estimate. Specifically, past approaches modeled each of K sensor individually with an AR model of lag p, requiring a total of pK parameters, whereas the joint multivariate framework requires $O(pK^2)$ parameters. This becomes a significant concern due to the large number of sensors (K) being generated by massive modern SHM implementations which are becoming economically practical with the continuing evolution of low-cost sensing hardware. As an example, various bridges in Hong Kong currently have monitoring systems with sensors counts ranging from several hundred to more than 1500 [39]. Further, processing is typically performed directly on this hardware (an example of which is shown in Fig. 1), making reduced computation a high priority even for moderate K. We cope with this problem by using graphical models to enforce sparsity on the parameters in a way that agrees with knowledge of the system (see for example [22,25,23]).

The remainder of the paper is structured as follows: we begin by showing how Bayesian vector autoregressive (BVAR) models – a tool developed and used primarily in econometrics [26] – are a natural method for modeling SHM systems; we demonstrate this through the use of a simulated example. We then propose the use of graphical models to exploit sparsity in