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A Bayesian state-space approach for damage detection and classification

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A B S T R A C T

The problem of automatic damage detection in civil structures is complex and requires a system that can interpret collected sensor data into meaningful information. We apply our recently developed switching Bayesian model for dependency analysis to the problems of damage detection and classification. The model relies on a state-space approach that accounts for noisy measurement processes and missing data, which also infers the statistical temporal dependency between measurement locations signifying the potential flow of information within the structure. A Gibbs sampling algorithm is used to simultaneously infer the latent states, parameters of the state dynamics, the dependence graph, and any changes in behavior. By employing a fully Bayesian approach, we are able to characterize uncertainty in these variables via their posterior distribution and provide probabilistic estimates of the occurrence of damage or a specific damage scenario. We also implement a single class classification method which is more realistic for most real world situations where training data for a damaged structure is not available. We demonstrate the methodology with experimental test data from a laboratory model structure and accelerometer data from a real world structure during different environmental and excitation conditions.

1. Introduction

Structural inspection has been necessary to ensure the integrity of infrastructure for almost as long as structures have existed, ranging from informal subjective methods such as visual or hammer testing, to quantitative modern methods including ultrasound, X-ray, and radar non-destructive testing techniques. These testing methods are relatively intensive as they depend on the experience of the inspector and the time to inspect suspected damaged locations in the structure. Inspections are typically carried out periodically, however if additional sensors were added to the structure they might provide an extra indication of where and when potential damage occurs, reducing the time and effort necessary for structural inspection.

Structural health monitoring (SHM) involves instrumenting a structure with sensors and deriving some information from the data they collect in order to determine if the structure has changed [1]. This change in the structure could then be attributed to some sort of damage that would be more closely investigated. In general, data is processed into features that may indicate these changes in the structure and in some cases statistical discrimination of these features are used to separate data collected from intact and changed structures [2]. Statistical or similar methods are essential for being able to discriminate feature changes as a result of structural changes from measurement or environmental variability.

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Bayesian inference is a probabilistic method of inference that allows one to form probabilistic estimates of certain parameters given a series of observations. The method can be used in a couple of different ways in SHM including model updating of structural parameters [3], monitoring by inferring structural parameters over time [4], and determining the optimal placement of sensors [5]. Bayesian inference can be used in either a model-based situation where a structural model is either formulated or updated as a basis for damage detection, a data-based situation where there is no prior information on the structural model and only the sensor data is used, or a mixture of the two situations.

We apply a recently developed framework for Bayesian switching dependence analysis under uncertainty [6] to time-series data obtained from accelerometers located at multiple positions on a building for the purposes of structural damage detection and classification. This model is effectively a computational representation of not only the physical structural system, but also the act of collecting information on that system through the use of sensors. By accounting for interactions between sensor signals collected from the system in different locations, the hope is to infer a representation of the structural connections between locations in the structure or the underlying physics without having any knowledge of the actual structural configuration or dynamics. Assuming that the model learned from a set of data is exclusive to the corresponding physical structural configuration and condition, a change in the model parameters could be indicative of a change in the measured physical structure which might be caused by damage.

In order to see if these assumptions might hold true, we test the methodology on data from a laboratory model structure in various intact and damaged conditions, as well as on data from a real building under ambient and non-ambient conditions, such as during a fireworks show and a small earthquake. These data consist of short sequences of measurements, such that it is unlikely that changes occur within a single sequence. The problem of damage detection can then be cast as a problem of time-series classification. If prior data from possible damage scenarios is available, then this problem is a standard multi-class classification problem. However, in most real scenarios, only data from an intact structure is available a priori. Then, the problem of damage detection can be seen as a single-class classification problem which we also implement. The primary contribution of this paper in extending the work of Dzunic et al. [6] is the application of the methodology as a structural health monitoring algorithm for damage detection. Building on the work presented in [7] involving multi-class classification, this paper also considers single-class classification as well as the inferred graphical model of a system. Additionally, another goal is to see if the inferred graphical model of the system may represent any physical characteristics of an instrumented structure.

In Theory (Section 2), we first provide background on Bayesian inference and graphical models in Section 2.1, then we describe the switching state-space interaction model of Dzunic et al. [6] in Section 2.2, and finally we develop extensions of this model for time-series classification in Section 2.3 and single-class classification in Section 2.4. We describe the experimental setup of a laboratory model structure and the Massachusetts Institute of Technology's Green building in Section 3. We present three sets of results in Section 4. The results of the interaction analysis, given in Section 4.1, indicate that inferred structures correlate significantly with actual physical structures and prior knowledge. Multi-class classification results, presented in Section 4.2, demonstrate that the classification model can classify time-series obtained under intact and different damage scenarios with high accuracy. Finally, single-class classification results, presented in Section 4.3, demonstrate that the single-class classification model detects with high accuracy time-series obtained under conditions that differ form intact or ambient conditions and that it also predicts the "strength of deviation". We finish with conclusions in Section 5.

2. Theory

In this section, we first provide relevant background on graphical models and Bayesian inference in Section 2.1. Then, we describe the state-space switching interaction model (SSIM) of [6] in Section 2.2 and its modifications for the applications to time-series classification in Section 2.3 and single-class classification in Section 2.4.

2.1. Background

The relevant background for this paper includes probabilistic graphical models (Bayesian networks and dynamic Bayesian networks in particular) and principles of Bayesian inference. An introduction to the Bayesian approach and Bayesian networks can be found in [8]. An introduction to dynamic Bayesian networks can be found in [9].

2.1.1. Graphical models

Graphical models are a language that uses graphs to compactly represent families of joint probability distributions among multiple variables that respect certain constraints dictated by a graph. There are two common types: undirected graphical models (also called Markov random fields) and directed graphical models (Bayesian networks), which use undirected and acyclic directed graphs, respectively, to form such constraints. In both cases, nodes of a graph correspond to the variables which joint distribution is modeled. In an undirected graphical model, a joint probability distribution is assumed to be proportional to a product of nonnegative functions (called potentials) over graph cliques (fully connected subgraphs). In a Bayesian network, a distribution is assumed to be a product of conditional distributions of each variable given its parents in the graph. Examples of both types of graphical models are shown in Fig. 1. In this paper, we use Bayesian networks and their variant, dynamic Bayesian networks. We now describe them in more detail.