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Pairwise graphical models for structural health monitoring with dense sensor arrays

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ABSTRACT

Through advances in sensor technology and development of camera-based measurement techniques, it has become affordable to obtain high spatial resolution data from structures. Although measured datasets become more informative by increasing the number of sensors, the spatial dependencies between sensor data are increased at the same time. Therefore, appropriate data analysis techniques are needed to handle the inference problem in presence of these dependencies. In this paper, we propose a novel approach that uses graphical models (GM) for considering the spatial dependencies between sensor measurements in dense sensor networks or arrays to improve damage localization accuracy in structural health monitoring (SHM) application. Because there are always unobserved damaged states in this application, the available information is insufficient for learning the GMs. To overcome this challenge, we propose an approximated model that uses the mutual information between sensor measurements to learn the GMs. The study is backed by experimental validation of the method on two test structures. The first is a three-story two-bay steel model structure that is instrumented by MEMS accelerometers. The second experimental setup consists of a plate structure and a video camera to measure the displacement field of the plate. Our results show that considering the spatial dependencies by the proposed algorithm can significantly improve damage localization accuracy.

1. Introduction

Health monitoring functionality is an important aspect of smart structures in dealing with challenges associated with complexity, high operational demands, safety, maintenance, and environmental effects. The main difficulties in developing such systems are: (1) appropriate instrumentation of structures for acquiring informative data sets, and (2) providing efficient and robust data analysis algorithms for reliable decision making and uncertainty quantification (UQ). The instrumentation cost for studying structural dynamics beyond simple modal analysis was previously substantially high. Also, former studies showed that linear characterization of structural dynamics may not be sufficient for reliable damage detection [1–4]. Therefore, these two issues made it economically difficult to rationalize investing in monitoring systems.

Through advances in sensor technology, it is becoming less costly to instrument structures. In addition to mechanical sensors, recently developed novel video-based techniques, can provide spatially high resolution data sets by using video cameras [5–7]. Although the first challenge regarding the instrumentation of structures may be managed to an extent by these developments, additional complexities are introduced into decision making and UQ due to the computational demand of

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analyzing big data sets as well as the possible inducement of more uncertainties associated with the use of more sensors. This issue becomes more difficult to deal with when highly sensitive damage indicative features are used in methods such as the auto regressive (AR) based techniques [8,9], state-space reconstruction using the delay-coordinate method [10], nonlinear frequency response function technique [11–14], and energy-based feature extraction using the Hilbert-Huang transform (HHT) [4] are used for SHM. Due to their high sensitivity, these features tend to encode more redundant information. Ignoring the effect of these redundancies may cause problems such as increasing the false-positive (FP) alarms for a given true-positive (TP) rate. This motivates further investigation on new data analysis techniques with the capability of using robust damage sensitive features as well as considering the complex data structure provided by such features.

In this study we address the problem of reducing the FP ratio without significantly affecting the TP ratio in dense sensor networks by considering the spatial dependencies of sensor measurements. Our approach to do that is to use graphical models (GMs) which are strong mathematical tools for representing complex probability distributions and the dependencies between random variables (RV). Appropriately learning and efficiently making inference on GMs are the two main challenges in using these models in practice. Learning GMs is particularly more critical in SHM as it usually involves working with incomplete datasets which do not provide enough information for learning GMs through standard methods [15]. As a solution to this problem, we propose an approximated model for graph parameter learning that works based on the mutual information (MI) between different sensor data. By that, the contributions of this study can be summarized as (1) improving damage localization resolution in dense sensor arrays by using GMs, and (2) proposing an approximated model that uses information analytics to learn the graph parameters. The body of this work starts with formalizing the SHM problem and the objectives of this study. Section 3 reviews undirected GMs as the main mathematical tool that we use in this study and in Section 4 we explain the details of our proposed algorithm. As mentioned previously, the main application of this work is to analyze dense sensor networks. Therefore, a discussion on obtaining spatially high resolution datasets with a focus on camera-based data acquisition technique, used in this study, is provided in Section 5. Finally, the experimental validation is presented in Section 6 by testing various sensor systems and comparing different damage detection algorithms.

2. Formalizing SHM problems

Consider a structure that is instrumented by s number of sensors. Assume the feature matrix associated with the ith sensor data that is obtained by testing the intact structure n_b times is

$$\mathbf{y}_i^b = \left[\underline{y}_{i1}^b, \underline{y}_{i2}^b, \ldots, \underline{y}_{im}^b\right] \tag{1}$$

where m is the total number of damage sensitive features and each $\underline{y}_{il}^b,\ l = 1, \ldots, m$, is a $n_b \times 1$ vector. Note that throughout the paper, RVs are denoted by a sans-serif font, e.g. x, and the realization of those variables are denoted by serifed fonts, e.g. x. Similar to $\mathbf{y}_i^b$, the feature matrix $\mathbf{y}_i^u$ can be obtained from a new set of tests on the structure at an unknown state. If there is information available from some damage scenarios, the corresponding feature matrix is defined similarly and denoted by $\mathbf{y}_i^d$. The superscripts u an d respectively denote *unknown state* and *damaged*. The number of corresponding tests is assumed to be n_u and n_d. In addition to these real-valued quantities, consider a set of discrete RV $\mathbf{x}$ as

$$\mathbf{x} = [\mathsf{x}_1, \mathsf{x}_2, \ldots, \mathsf{x}_s] \tag{2}$$

where $\mathsf{x}_i,\ i = 1, \ldots, s$, takes the values 0 or 1 if the structure is respectively intact or damaged at the ith sensor location. For notation simplicity, define:

$$\mathbf{Y}_S^b = \left\{\mathbf{y}_j^b | j \in S\right\}; \quad S \subseteq \{1, \ldots, s\} \tag{3}$$

which is a set that contains the feature matrices for a subset of sensors, S, for intact state of the structure. Similarly, $\mathbf{Y}_S^d$ and $\mathbf{Y}_S^u$ can be respectively defined by choosing a subset of all feature matrices $\mathbf{y}_i^d$ and $\mathbf{y}_i^u$.

As suggested by other studies on similar problems, consideration of dependencies of RVs may significantly improve the classification results [16,17]. Therefore, with the above definitions, the objective is considered as computing $p_{\mathsf{x}_i|\mathbf{Y}_{1:s}},\ \forall i \in \{1, \ldots, s\}$ which is the probability density of the states at each sensor location given the features at all sensor locations, $(S = \{1, \ldots, s\} = \{1 : s\})$. Fulfilling this objective requires the dependencies of the RVs to be considered. To do that in this study we use Markov Random Fields (MRF), described in the next section.

3. Graphical models for considering the dependencies of RVs

3.1. Graphical models

GMs are strong mathematical tools for representing complex probability distributions and conditional dependencies between RVs. Depending on the type of dependencies that we want to model, we can use either directed acyclic graphs (DAG), factor graphs, or undirected graphs (UGM). The first two types of GM are mostly used for modeling the induced dependencies between the RVs and their ordering [15]. Such dependencies are not of central importance in this study; thus,