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Sparsity-based approaches for damage detection in plates

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ABSTRACT

The data deluge in Structural Health Monitoring (SHM) and the need for automated online damage detection systems necessitates a move away from traditional model-based approaches. To that end, we propose sparsity-based algorithms for damage detection in plates. Instead of high-fidelity models, our proposed algorithms use *dictionaries*, consisting of response signals acquired directly from the system of interest, as the key feature to both detect and localize damages. We address the damage detection problem both when the damage is located *on* or *off* a grid of possible damage coordinates defined by the dictionary. This gives rise to two classes of problems, namely, *on the grid* and *off the grid* problems. In our sparsity-based on the grid damage detection (SDD-ON) platform, we solve a LASSO regression problem, where, the unknown vector is a pointer for existence of damage at the various locations defined on the grid used for dictionary construction. In our proposed off the grid damage detection (SDD-OFF) platform, we use a penalized regression algorithm to extend the dictionary of measured damage signals to points off-the-grid by linear interpolation. We evaluate the performance of both SDD frameworks, in detecting damages on plates, using finite element simulations as well as laboratory experiments involving a pitch-catch setup using a single actuator-sensor pair. Our results suggest that the proposed algorithms perform damage detection in plates efficiently. We obtain area under receiver operating characteristic (ROC) curves of 0.997 and 0.8314 for SDD-ON and SDD-OFF, respectively.

1. Introduction

Structural Health Monitoring (SHM) is an essential component of maintenance for engineering systems. The research community has contributed vastly to this field over the past three decades, aiming to improve the efficiency and accuracy of detection and localization of damages in engineered systems [1,2]. In the past few years, significant strides have been made in data transmission and acquisition systems [3] for developing efficient SHM systems [4,5]. These improvements have led to a massive increase in the volume of data collected from engineered systems. This further opens the possibility of using more data, instead of detailed models, for damage detection [6].

Traditionally, a class of SHM approaches involve the development of detailed structural models for studying the behavior of structural systems in both pristine and damaged conditions [7]. One performs damage detection using features, extracted

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from the models, that best define the changes in the behavior of systems from a pristine to damaged condition. However, modeling complicated systems is challenging. Capturing the physics of a system accurately in terms of behavior of all degrees of freedom involved and modeling of specialized boundary conditions pose a significant obstacle to a designer. Although, creating such high fidelity models is possible using advanced simulation softwares, analyzing them becomes computationally prohibitive. For example, in this study, the Guided Ultrasonic Waves (GUW)-based damage detection is used. The advantages of GUW-based damage detection [8–10] over traditional vibration-based techniques [11] is well-addressed in the literature [12], with the key advantage being its ability to detect, localize and quantify minute damages. In spite of these advantages, from an experimental standpoint, it requires a heavy computational effort for simulating the waves propagating in a structural system. Gopalakrishnan [13] discusses the various computational issues involved in modeling wave propagation problems using the finite element method.

Recently, the applications of statistical learning algorithms for damage detection, has received significant attention [6,14–16]. In such approaches, statistical learning algorithms are used to construct surrogate models [17] that overcome the need for developing high-fidelity models of systems. Statistical learning algorithms are well equipped for handling large data sets of signals generated by a dense array of sensors deployed on a system. Support Vector Machines (SVM) [18] and Artificial Neural Networks (ANN) [19] are the most widely used data-intensive approaches for damage detection using guided waves. A review of such methods can be found in Raghavan and Cesnik [10]. However, these techniques require extensive training for damage classification and localization. In addition, the amount of training data vastly increases for achieving high resolution in damage localization. In this paper, we propose platforms, that harness the inherent sparsity in the damage detection and localization problem and achieve this by minimal *a priori*data acquisition.

We propose sparsity-based detection algorithms, that avoid modeling of the real system at hand. Here, we construct a damage location indicator vector $\mathbf{x}$. Under the assumption that the number of possible damage locations, at a certain instant of time in a system, is small, the vector $\mathbf{x}$ will have very few non-zero elements. A k-sparse vector $\mathbf{x}$ is defined as a vector of length n with k nonzero entries, where $k \ll n$. We associate a matrix, known as the *dictionary*, with the damage location indicator vector $\mathbf{x}$ and call it the Damage Characterization Matrix (DCM). As shown in Fig. 1, the DCM consists of signals acquired from the identical system with changing damage locations. Since, DCM captures the behavior of the system for different locations of damage, it alleviates the need for high fidelity models representing the system. Existing sparse representation-based methods still use a physics-based wave propagation model for dictionary construction [20,21]. However, we circumvent the need of such models by directly using acquired data for constructing the dictionary. The data reflects the dynamics of the system as well as possible changes due to presence of a damage. From a system identification point of view, the inherent physics involved in the elements of the DCM ensure that the proposed framework is not a black-box method, but closer to a gray-box approach.

Clearly the efficacy of the proposed dictionary-based approaches depend on the efficiency of the DCM. Two possibilities arise; the first is when a grid of locations are selected such that they represent the most probable locations of damage in the system. The second is when the number of possible damage locations is large enough rendering the construction of the DCM

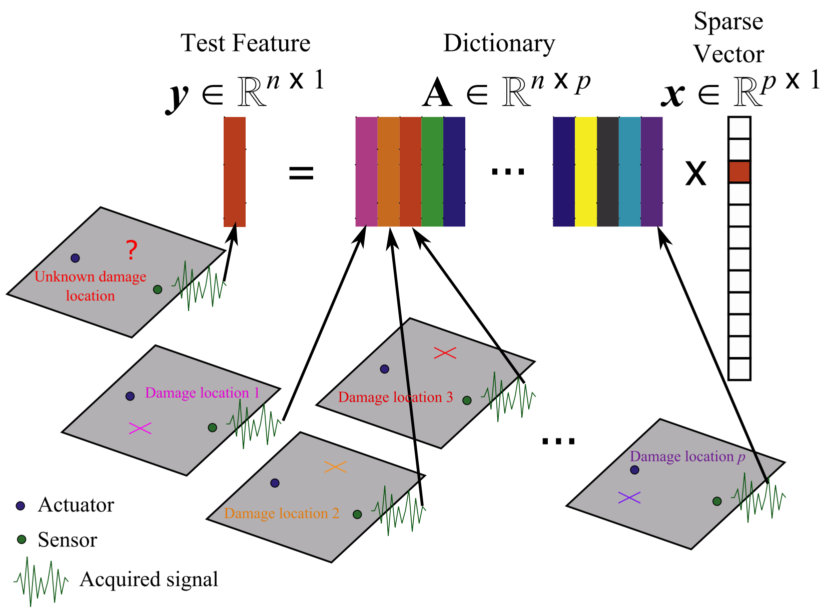

Fig. 1. Illustration of SDD-ON for damage detection. Each element of the dictionary is constructed using processed acquired signals from different damage locations as shown. In this case the unknown damage location, from the test vector $\mathbf{y}$, is location 3. Hence, the third element of the sparse vector $\mathbf{x}$, evaluated by sparse regression, points to location 3 in the dictionary $\mathbf{A}$ (DCM).