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Algorithm for damage detection in wind turbine blades using a hybrid dense sensor network with feature level data fusion

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ABSTRACT

Damage detection in wind turbine blades requires the ability to distinguish local faults over a global area. The implementation of dense sensor networks provides a solution to this local-global monitoring challenge. Here the authors propose a hybrid dense sensor network consisting of capacitive-based thin-film sensors for monitoring the additive strain over large areas and fiber Bragg grating sensors for enforcing boundary conditions. This hybrid dense sensor network is leveraged to derive a data-driven damage detection and localization method for wind turbine blades. In the proposed method, the blade's complex geometry is divided into less geometrically complex sections. Orthogonal strain maps are reconstructed from the sectioned hybrid dense sensor network by assuming different bidirectional shape functions and are solved using the least squares estimator. The error between the estimated strain maps and measured strains is extracted to define damage detection features that are dependent on the selected shape functions. This technique fuses sensor data into a single damage detection feature, providing a simple and robust method for inspecting large numbers of sensors without the need for complex model driven approaches. Numerical simulations demonstrate the proposed method's capability to distinguish healthy sections from possibly damaged sections on simplified 2D geometries.

1. Introduction

Wind energy growth is driven at the nexus of public policy and economics (Borenstein, 2012). As with most renewable energy projects, a wind farm's economic viability typically relies on public subsidies, a predictable energy source, and mature and reliable technology (Afanasyeva et al., 2016). The economic evaluation of wind projects is particularly challenging due to the unpredictable operation and maintenance (O&M) costs. O&M traditionally includes the cost of all necessary repairs and replacements. The estimation of O&M costs for wind generating facilities is difficult as operational lifetime data is insufficient or inapplicable to the quickly evolving energy infrastructure. Therefore, O&M costs are estimated on a cost per MW hours basis, allowing owners to share O&M costs across multiple turbines. However, this practice is less convenient for operators of small wind farms where the ability to hedge cost is difficult (Celik, 2003), for operators of wind farms in micro grids where downtime is often compensated for with expensive fossil fuels (VanderMeer and Mueller-Stoffels, 2014), and for operators of wind farms in the offshore environment where the cost structure is often largely unknown (Cockerill et al., 2001).

Reduction of uncertainty related to the O&M of a wind turbine structural system (Ghoshal et al., 2000) and the enabling of prognostics and health management (PHM) (Richards et al., 2015; Ekelund, 2000) is therefore of interest to wind farm owners and operators. Monitoring the mesostructures (e.g. towers and blades) of wind turbines is difficult due to the need to distinguish between faults in the structure's global (e.g. changing load paths, loss in global stiffness) and local (e.g. crack propagation, composite delamination) conditions (Ghoshal et al., 2000). Traditional approaches for structural health monitoring (SHM) of wind turbine blades have focused on monitoring the structure using a limited number of sensors and applying a variety of post-processing techniques (Gross et al., 1999). However, these techniques often lack the ability to distinguish local failures from global events and demonstrated a limited damage localization ability (Zou et al., 2000).

A logical solution to the local/global detection problem is to simply increase the number of sensors in the monitored structure by creating dense sensor networks (DSNs). These networks, often termed electronic artificial skins, e-skins or sensing skins, are thin electronic sheets that

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mimic the ability of biological skin to detect and localize damage. Sensing skins often consist of rigid or semi-rigid cells mounted on a flexible sheet, as demonstrated by Xu et al. (2003) and Lee et al. (2006). Recent developments in sensing skins have progressed towards the development of microelectromechanical systems (MEMS) mounted in flexible sheets without the need for rigid packaging (Mahmood et al., 2015). Sensing skins with the transducing sensor built into the skin have been proposed (Chang et al., 2008). Additionally, Sensing skins with integrated electronics for signal processing have also been introduced (Yao and Glisic, 2015). These integrated sensing skins offer the potential to enable low-cost direct sensing and can be scaled for the monitoring of mesoscale systems, including wind turbine blades. Schulz et al. have proposed the use of a dense sensor network of series-connected piezoceramic (PZT) nodes for the continuous monitoring of wind turbine blades Schulz and Sundaresan (2006). The densest deployment of sensors for the SHM of wind turbine blades known to the authors was done by Rumsey et al. at Sandia National Laboratories Rumsey and Paquette (2008). Various sensor technologies were investigated for the potential of monitoring a composite blade's structural condition during a fatigue test. Generally, successful damage detection was found to require optimal sensor placement, synchronization of sampling between different sensor types, and having sensor technology capable of detecting damage that occurs on a small scale while being able to be distributed as an array over the entire structure.

Leveraging recent advances in the field of flexible electronics (Rogers et al., 2010), the authors have developed a sensing skin termed the soft elastomeric capacitor (SEC). Developed around an inexpensive nanocomposite based on a styrene-co-ethylene-co-butylene-co-styrene (SEBS) block co-polymer, the SEC is a low-cost sensor customizable in shape and size (Laflamme et al., 2013a). Its static (Laflamme et al., 2013b) and dynamic (Laflamme et al., 2015) behaviors have been characterized, including numerical and experimental damage detection applications to wind turbine blades (Laflamme et al., 2016; Downey et al., 2017). Additionally, the effectiveness of a DSN consisting of SECs for detecting fatigue cracks has been demonstrated (Kharroub et al., 2015). A particularity useful attribute of the SEC is its ability to measure additive in-plane strain, and therefore, its signal must be decomposed into orthogonal directions if one desires to reconstruct uni-directional strain maps.

With the advancement of low-cost, high-channel-count sensing skins, damage detection and data-fusion techniques need to be developed to provide SHM and PHM capabilities based on this unique class of sensors. Data fusion consists of the integration of sensor data from a multitude of sources in order to make a useful representation of the monitored systems. This representation should be of sufficient quality to assist in forming a damage detection, localization, and quantification decision. Additionally, data fusion can be used to obtain a damage detection feature from multiple sensors that is informative and non-redundant. In the case of SHM, features should allow for the distinction between a damaged and an undamaged state. Examples found in the literature are most commonly based on measured dynamic signals such as resonant frequencies, mode shapes, or properties derived from mode shapes (Zou et al., 2000; Sohn et al., 2003; Han et al., 2006).

This work introduces a computationally efficient data fusion technique that is capable of monitoring mesoscale structures without associated models or historical datasets. More specifically, the proposed NeRF (Network Reconstruction Feature) algorithm is capable of classifying hybrid dense sensor networks (HDSN) sections into healthy, or containing potential damage. This work uses HDSNs consisting of SECs for covering the large areas of a blade and Fiber Bragg grating (FBG) sensors for the enforcement of boundary conditions along the edges of sections and the separation of monitored sections. The SEC is used throughout this work as a large area electronic strain transducer. However, similarly developed large area electronics optimized for strain measurements could also be used (Yao and Glisic, 2015; Burton et al., 2016).

The NeRF algorithm works through comparing an individual sensor's measured state with the estimated response within an HDSN section. This response is built through assuming a shape function and using the least squares estimator (LSE) to approximate uni-directional strain maps. An error function is introduced, which is defined as the mean square error (MSE) between the sensor's measured and estimated strains. Thereafter, features are defined as the change in error associated with a given increase in the shape function's complexity. This technique fuses the SEC and FBG strain data into a single damage detection feature, providing a simple and robust method for inspecting large numbers of sensors without necessitating complex physical models.

The contributions of this work are three-fold: 1) an algorithm for the development of a damage detection feature that integrates data from a newly proposed HDSN into a single detection value is introduced; 2) a demonstration of the damage detection feature's ability to detect, quantify and localize damage; and 3) the evaluation of the damage detection feature's capabilities without relying on models or historical datasets. This paper is organized as follows. Section 2 introduces the SEC along with relevant background including the strain decomposition algorithm previously developed. Section 3 introduces the NeRF algorithms simulations used for validation. Section 4 presents the numerical models used for the simulations. Section 5 discusses the simulation results. Section 6 concludes the paper.

2. Background

This section provides background on the SEC sensor along with a brief review of the extended LSE algorithm for decomposing the SEC additive in-plane strain signal.

2.1. Soft elastomeric capacitor

The SEC is a thin film, large area sensor that transduces a change in its geometry (i.e., the monitored substrate strain) into a change in capacitance. The SEC measures in-plane strain ($x-y$ plane in Fig. 1(insert)). The fabrication process of the SEC is documented in Laflamme et al. (2013a). Briefly, the dielectric is fabricated from an SEBS block co-polymer filled with titania to enhance its durability and permittivity. The conductive plates are fabricated from an SEBS filled with carbon black particles. The SEC is a highly scalable technology, because it uses only commercially available and inexpensive materials and its

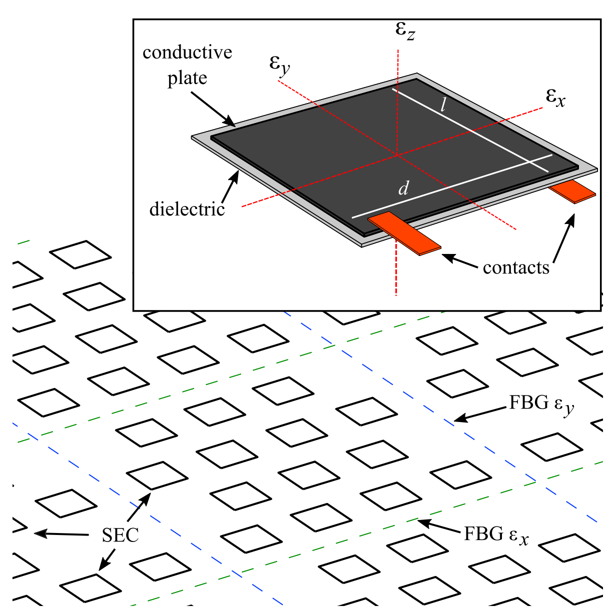

Fig. 1. HDSN technology: HDSN section with FBG sensors enforcing strain boundary conditions and SECs providing large area sensing coverage; insert: annotated SEC sensor with reference axes.