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On multi-site damage identification using single-site training data

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ABSTRACT

This paper proposes a methodology for developing multi-site damage location systems for engineering structures that can be trained using single-site damaged state data only. The methodology involves training a sequence of binary classifiers based upon single-site damage data and combining the developed classifiers into a robust multi-class damage locator. In this way, the multi-site damage identification problem may be decomposed into a sequence of binary decisions. In this paper Support Vector Classifiers are adopted as the means of making these binary decisions. The proposed methodology represents an advancement on the state of the art in the field of multi-site damage identification which require either: (1) full damaged state data from single- and multi-site damage cases or (2) the development of a physics-based model to make multi-site model predictions. The potential benefit of the proposed methodology is that a significantly reduced number of recorded damage states may be required in order to train a multi-site damage locator without recourse to physics-based model predictions. In this paper it is first demonstrated that Support Vector Classification represents an appropriate approach to the multi-site damage location problem, with methods for combining binary classifiers discussed. Next, the proposed methodology is demonstrated and evaluated through application to a real engineering structure – a Piper Tomahawk trainer aircraft wing – with its performance compared to classifiers trained using the full damaged-state dataset.

1. Introduction

Structural Health Monitoring (SHM) refers to the process of measuring and interpreting *in situ* data acquired from a structural system in order to objectively quantify the condition of the structure. SHM has the potential to offer substantial economic and life-safety benefits for aerospace and civil structures in applications as diverse as civil and military aircraft, civil infrastructure, energy generation and offshore structures. The three motivating aspects for SHM that are recurrently mentioned in the literature are: (1) the life-safety benefits achievable through being able to continuously monitor safety-critical components. (2) the economic benefits achievable through avoiding unplanned down-time and increasing the efficiency of inspection and maintenance, and (3) the ability to optimise newly designed structures for which the current health condition is known through monitoring [1]. The damage identification problem can usefully be considered as a hierarchical process, developed from that discussed by Rytter [2], that progresses from the detection of the occurrence of

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damage; to localisation of where damage has occurred; to classification of the type of damage that is present; assessment of the damage extent; and finally prediction of the residual life of the system in light of the damage.

The focus of this study is on the second level of this hierarchy - localisation - and in particular the problem of identifying changes in the structure that have occurred at multiple locations. Multi-site damage identification represents an important and challenging problem in SHM but one that has received comparatively little dedicated attention in the literature, with the majority of approaches presented in the literature (see, for example, the extensive reviews in [3,4]) focusing on the identification of single-site damage. The impact of this restriction is clear given that an *in situ* structure would be expected, over time, to exhibit degradation from its baseline state concurrently at multiple locations. Any practical application of SHM should be able to account for this fact, with systems that do not do so potentially unable to accurately describe the true health state of the structure.

Approaches to Structural Health Monitoring may be broadly separated into two classes: *data-based* approaches that follow a statistical pattern recognition paradigm and rely solely on experimental data; and *model-based* approaches that make use of the predictions of a representative physics-based model of the structure, typically by applying a Finite Element (FE) model updating procedure. While the problem of multiple damage location from a purely data-based perspective has received very little dedicated attention in the literature, FE model updating is, at least in principle, appropriate to the multiple damage location task. The solution procedure typically involves minimisation of residuals between damage-sensitive *features* drawn from the experimental structure and the predictions of the model. Ruotolo and Surace [5] presented an early study of this type focusing on multiple damage location and assessment in a cantilever beams, with a weighted sum of modal features (natural frequencies, modal curvatures and mass-normalised modeshapes) adopted as the objective function to be minimised. A similar approach, the Multiple Damage Location Criterion (MDLAC), is presented by Contursi et al [6], with the cross-correlation between measured and theoretical natural frequencies adopted as the objective function and applied to multi-site damage. An incremental development of the MDLAC approach is presented in [7] with damage location pursued using Dempster-Shafer evidence theory, allowing fusion of the results of frequency MDLAC and modeshape MDLAC outcomes, and a micro-search genetic algorithm used to estimate damage extent.

Dealing with the uncertainty that arises from physical variability, experimental variability and model-form error presents a major issue for FE updating approaches. In recent years this has led to increased interest in methods that explicitly account for uncertainty, with both probabilistic methods (for example Bayesian updating [8,9]), and non-probabilistic methods (for example fuzzy updating [10]) methods demonstrating considerable success for single-site damage location. Nonetheless, challenges remain. The principal drawback of the approach is that developing a finite element model of a complex engineering structure sufficient to reliably predict response changes due to damage is a difficult and potentially expensive task, as evidenced by growth of interest in the fields of model validation and uncertainty quantification within structural dynamics. Secondly, a potentially onerous number of model executions may be required to fully explore the parameter space during the updating step, although approaches such as parameter subset selection may go some way towards addressing this [11]. It is noted that in cases where experimental examples have been used to illustrate approaches they have typically exhibited a low level of complexity, for example cantilever beams and truss-type structures. It is also noted that appropriately thorough consideration of the impact of numerical and experimental uncertainty remains comparatively rare.

Data-based methods – as typically applied – initially appear less well suited to the multi-class damage location task than model-based methods. Damage location via a statistical pattern recognition (SPR) paradigm requires the adoption of a supervised learning approach, thus requiring the gathering of data from the structure in both its undamaged and damaged state [12]. Localisation is pursued by evaluating the difference between the current state of the structure and an initial baseline state that is representative of the undamaged structure. A feature vector is thus formed that may be compared to previously acquired, labelled observations in order to diagnose the state of the structure by applying a classification algorithm. The major drawback of the data-based approach to SHM is the requirement to have access to structural data for all damage states of interest, which is rarely available even for single-site damage. However, a major advantage of this approach is in the handling of uncertainty. Provided the training set contains data representative of the variability that will be seen in the monitoring phase, this variability will be accounted for be any appropriately trained classifier. Manson et al [13] present one such successful example of single-site damage location based upon features drawn from transmissibility spectra, with classification performed using artificial neural networks (ANNs). It is noted that there is a caveat to the requirement for damage state data in cases where the adopted feature exhibits sensitivity to local damage, and some success has been reported using, for example, modeshape curvatures [14]. Nonetheless, such features exhibit disadvantages alongside advantages (susceptibly to experimental noise being an example in the case of modeshape curvatures) and there is clear motivation for developing methods for multi-site damage location that maintain generality of feature choice.

The requirement to have access to structural data for all damage states of interest presents a critical constraint when considering classification of multi-site damage. In the case that damage is believed to occur at only one of a finite discrete set of n locations, the requirement is that data should be acquired for each of the corresponding n damage states. In the more general case of damage occurring concurrently at more than one location, the naïve approach might be to gather damage data for all combinations of damage location. However, the number of states for which data would be required in order to cover all combinations would be 2^n (including the undamaged state), and so grows exponentially with the number of locations n. Even in a more restrictive case where classification of up to k damage locations from the full set of n locations is sought, the number of damaged states for which data would be required is $\sum_{i=1}^{k} n!/(i!(n-1)!)$. For illustration, consider as an example a structure with $n = 10$ damage states of interest, perhaps representing particular locations on the surface of a