Chapter 8

Statistical Approach to Structural Damage Diagnosis under Uncertainty

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ABSTRACT

This chapter presents a statistical methodology for structural damage diagnosis (detection, localization and estimation), in the context of continuous online monitoring. There are several sources of uncertainty such as physical variability, measurement uncertainty and model errors that affect structural damage diagnosis, and therefore, it may not be possible to precisely detect, localize, and estimate damage. Hence, a statistical approach can help to identify these sources of uncertainty, quantify their combined effect on diagnosis, and thereby, provide an estimate of the confidence in the results of diagnosis. Damage detection is based on residuals between nominal and damaged system-level responses, using statistical hypothesis testing whose uncertainty can be captured easily. Localization is based on the comparison of damage signatures derived from the system model. Both classical statistics-based methods and Bayesian statistics-based methods are investigated to quantify the uncertainty in all the three steps of diagnosis, i.e. detection, localization, and quantification. While classical statistics-based methods use the concept of least squares-based optimization, Bayesian methods make use of likelihood function and Bayes theorem. The uncertainties in damage detection, isolation and quantification are combined to quantify the overall uncertainty in diagnosis. The proposed methods are illustrated using the example of a structural frame.

INTRODUCTION

Structural Health Monitoring (SHM) refers to the process of developing and implementing a damage identification strategy for structural applications in civil, aerospace, and mechanical domains (Farrar & Worden, 2007). Structural health monitoring techniques play a vital role in different types of practical
engineering applications, because they can be used to monitor the performance of these applications and aid several types of operational decision-making activities. This is established through the use of a combination of strategically placed array of sensors and a variety of mathematical methods and techniques, all of which constitute the overall structural health monitoring system.

An ideal structural health monitoring system is expected to facilitate automated continuous monitoring and diagnosis, thereby enabling prognosis and online health management. Damage diagnosis consists of three major steps – damage detection, damage localization (or isolation), and damage quantification. The first step of damage detection attempts to detect abnormalities in the structure and finds out if there has been any structural damage or deterioration. The second step of localization focuses on identifying that component(s) of the overall structure that has been subjected to damage. The third step of damage quantification quantifies the extent of damage, for example, estimating the reduction of stiffness in a structural member.

Several structural systems are complex in nature and consist of several members and components. Usually, only a few response quantities are monitored by the SHM system, but the number of prospective damage candidates is very high. In such cases, it is almost impossible to achieve precise damage diagnosis. Further, the inputs to the system, the physical parameters, sensor measurements, etc., may all be uncertain. While some of these sources of uncertainty are aleatory (irreducible sources of uncertainty), some of them are epistemic in nature (reducible). Due to the presence of these uncertainties, the behavior of these structural systems is uncertain in nature; it is important to account for these uncertainties while modeling the corresponding structural system response. As a result, the model predictions are uncertain. In addition, the experimental data may not be certain due to the presence of sensor noise, bias, or gain. Therefore, when both uncertain experimental data and uncertain models are both used for damage diagnosis, it is natural that the results of diagnosis are also uncertain.

Sankararaman and Mahadevan (Sankararaman & Mahadevan, 2011, 2013) explain that it is important to quantify the effect of the different sources of uncertainty and estimate the confidence in damage diagnosis by quantifying the uncertainty in damage detection, localization, and estimation, and the overall uncertainty in diagnosis. Such quantification of uncertainty in damage diagnosis is an essential step to guide decision-making regarding the functioning of the overall structural system.

In several research articles, the uncertainty in diagnosis (Achenbach, 2000) has been previously addressed using non-destructive evaluation (NDE) techniques, by estimating the probability of detection (POD). In such POD calculations, nominally identical damage is introduced in a number of nominally identical specimens, and the number of successful detections is used to calculate the probability of detection. Such an approach is completely different from the goal in structural health monitoring where the focus is on one structural system that is being monitored. Further, it is not possible to perform repeated tests since the goal in SHM is to make use of monitoring data in order to diagnose damage that has been caused due to external sources.

System identification techniques have been pursued by several researchers for the purpose of damage isolation and quantification. Fundamentally, these methods could be viewed as statistical calibration problems where the model parameters are calibrated and the uncertainty in calibration can be expressed through confidence bounds in the parameter estimation. Several studies have investigated classical statistics-based methods (Dalai, Weyer, & Campi, 2005; Vuerinckx, Pintelon, Schoukens, & Rolain, 2001) and Bayesian methods (Ching, Beck, & Porter, 2006; Jiang & Mahadevan, 2008a; Peterka, 1981; Vanik, Beck, & Au, 2000) in system identification and structural health monitoring. These methods involve estimating all the system parameters simultaneously; this makes the computation time-consuming.