# Data Mining for Damage Detection in Engineering Structures

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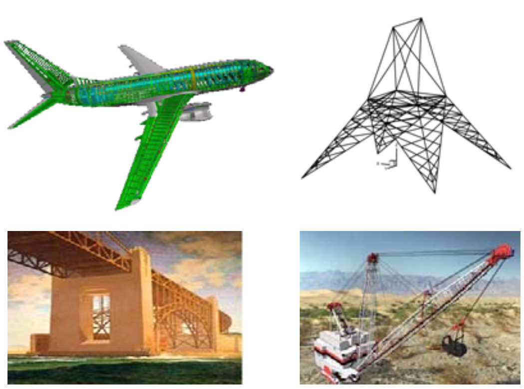
## INTRODUCTION

The process of implementing and maintaining a structural health monitoring system consists of operational evaluation, data processing, damage detection, and life prediction of structures. This process involves the observation of a structure over a period of time using continuous or periodic monitoring of spaced measurements, the extraction of features from these measurements, and the analysis of these features to determine the current state of health of the system. Such health monitoring systems are common for bridge structures, and many examples are citied in (Maalej et al., 2002).

The phenomenon of damage in structures includes localized softening or cracks in a certain neighborhood of a structural component due to high operational loads, or the presence of flaws due to manufacturing defects. Methods that detect damage in the structure are useful for non-destructive evaluations that typically are employed in agile manufacturing and rapid prototyping systems. In addition, there are a number of structures, such as turbine blades, suspension bridges, skyscrapers, aircraft structures, and various structures deployed in space, for which structural integrity is of paramount concern (Figure 1). With the increasing demand for safety and reliability of aerospace, mechanical and civilian structures damage detection techniques become critical to reliable prediction of damage in these structural systems.

*Figure 1. Damage detection is part of structural health monitoring system*



The most currently used damage detection methods are manual, such as tap test, visual, or specially localized measurement techniques (Doherty, 1997). These techniques require that the location of the damage be on the surface of the structure. In addition, location of the damage has to be known *a priori*, and these locations have to be readily accessible. This makes current maintenance procedure of large structural systems very time consuming and expensive due to its heavy reliance on human labor.

## BACKGROUND

The damage in structures and structural systems is defined through comparison of two different states of the system; the first one is the initial undamaged state, and the second one is the damaged state. Due to the changes in the properties of the structure or quantities derived from these properties, the process of damage detection eventually reduces to a form of pattern recognition/data mining problem. In addition, emerging continuous monitoring of an instrumented structural system often results in the accumulation of a large amount of data that need to be processed, analyzed, and interpreted for feature extraction in an efficient damage detection system. However, the rate of accumulating such data sets far outstrips the ability to analyze them manually. More specifically, there is often information hidden in the data that cannot be discovered manually. As a result, there is a need to develop an intelligent data processing component that can significantly improve the current damage detection systems. An immediate alternative is to design data mining techniques that can enable real-time prediction and identification of damage for newly available test data, once a sufficiently accurate model is developed.

In recent years, various data mining techniques, such as artificial neural networks (ANNs) (Anderson, Lemoine

& Ambur, 2003; Lazarevic et al., 2004; Ni, Wang & Ko, 2002; Sandhu et al., 2001; Yun & Bahng, 2000; Zhao, Ivan & DeWolf, 1998), support vector machines (SVMs) (Mita & Hagiwara 2003), decision trees (Sandhu et al., 2001), have been applied successfully to structural damage detection problems, thus showing that they can be potentially useful for such class of problems. This success can be attributed to numerous disciplines integrated with data mining, such as pattern recognition, machine learning, and statistics. In addition, it is well known that data mining techniques effectively can handle noisy, partially incomplete, and faulty data, which is particularly useful, since in damage detection applications, measured data are expected to be incomplete, noisy, and corrupted.

The intent of this paper is to provide a survey of emerging data mining techniques for damage detection structures. Although the field of damage detection is very broad and consists of vast literature that is not based on data mining techniques, this survey will be focused predominantly on data mining techniques for damage detection based on changes in properties of the structure. However, a large amount of literature applicable to fault detection and diagnosis to application-specific system, such as rotating machinery, is not within the scope of this paper.

## CATEGORIZATION OF STRUCTURAL DAMAGE

The damage in structures can be classified as linear or nonlinear. Damage is considered as linear if the undamaged linear-elastic structure remains linear-elastic after damage. However, if the initially linear-elastic structure behaves in a nonlinear manner after the damage initiation, then the damage is considered as nonlinear. However, it is possible that the damage is linear at the damage initiation phase, but after prolonged growth in time, it may become nonlinear. For example, loose connections between the structures at the joints or the joints that rattle (Sekhar, 2003) are considered non-linear damages. Examples of such non-linear damage detection systems are described in Adams and Farrar (2002) and Kerschen and Golinval (2004).

Most of the modal data in the literature are proposed for the linear case. They are based on the following three levels of damage identification: (1) Recognition—-qualitative indication that damage might be present in the structure; (2) Localization—information about the probable location of the damage in the structure; and (3) Assessment—estimate of the extent of severity of the damage in the structure. Such linear damage detection techniques can be found in Yun and Bahng (2000), Ni, et al. (2002), and Lazarevic, et al. (2004).

## CLASSIFICATION OF DAMAGE DETECTION TECHNIQUES

We provide several different criteria for classification of damage detection techniques based on data mining.

In the first classification, damage detection techniques can be categorized into continuous (Keller & Ray, 2003) and periodic (Patsias & Staszewski, 2002) damage detection systems. Continuous techniques usually employ an integrated approach that consists of data acquisition process, feature extraction from large amounts of data collected from real-time sensors, and damage detection process. In periodic techniques, feature extraction process is optional, since the amount of data that need to be processed is not large and does not necessarily require data mining techniques for feature extraction.

In the second classification, we distinguish between application-based and application-independent techniques. Application-based techniques are generally applicable to a specific structural system, and they typically assume that the monitored structure responds in some predetermined manner that can be accurately modeled by (i) numerical techniques such as finite element (Sandhu et al., 2001) or boundary element analysis (Anderson, Lemoine & Ambur, 2003) and/or (ii) behavior of the response of the structures that are based on physics-based models (Keller & Ray, 2003). Most of damage detection techniques that exist in literature belong to the application-based approach, where the minimization of the residue between the experimental and the analytical model is built into the system. Often, this type of data is not available and can render application-based methods impractical for certain applications, particularly for structures that are designed and commissioned without such models. On the other hand, application-independent techniques do not depend on specific structure, and they are generally applicable to any structural system. However, the literature on these techniques is very sparse, and the research in this area is at a very nascent stage (Bernal & Gunes, 2000; Zang, Friswell & Imregun 2004).

In the third classification, damage detection techniques are split into signature-based and non-signature-based methods. Signature-based techniques extensively use signatures of known damages in the given structure that are provided by human experts. These techniques commonly fall into the category of recognition of damage detection, which only provides the qualitative indication that damage might be present in the structure (Friswell, Penny & Wilson, 1994) and, to a certain extent, the localization of the damage (Friswell, Penny & Garvey, 1997). Non-signature methods are not based on signatures of known damages, and they not only recognize but also localize and assess the extent of damage. Most of the damage detection techniques in the literature fall into this

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