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A Review of Structural Health Monitoring Literature 1996 – 2001

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ABSTRACT

Staff members at Los Alamos National Laboratory (LANL) produced a summary of the structural health monitoring literature in 1995. This presentation will summarize the outcome of an updated review covering the years 1996 - 2001. The updated review follows the LANL statistical pattern recognition paradigm for SHM, which addresses four topics: 1. Operational Evaluation; 2. Data Acquisition and Cleansing; 3. Feature Extraction; and 4. Statistical Modeling for Feature Discrimination. The literature has been reviewed based on how a particular study addresses these four topics. A significant observation from this review is that although there are many more SHM studies being reported, the investigators, in general, have not yet fully embraced the well-developed tools from statistical pattern recognition. As such, the discrimination procedures employed are often lacking the appropriate rigor necessary for this technology to evolve beyond demonstration problems carried out in laboratory setting.

1. INTRODUCTION

This paper provides a synopsis of a review [1] that will summarize structural health monitoring studies that have appeared in the technical literature between 1996 and 2001. The primary purpose of this review is to update a previous literature review [2, 3] on the same subject. As with these previous documents, this summary will not address structural health monitoring applied to rotating machinery or local nondestructive testing techniques. Instead, this review, as well as the previous one, focuses on global structural health monitoring.

This review begins by defining structural health monitoring process in terms of a statistical pattern recognition paradigm. The use of this paradigm in the literature review represents a significant change in the way this review is organized compared to the previous one. The critical issues for this technology that were identified at the completion of the previous review are then briefly summarized. In the first part of review, the literature is summarized in terms of how each study fits into the statistical pattern recognition paradigm. In the second portion, the literature is summarized with respect to the various applications that have been reported. This review concludes by attempting to summarize progress that has been made with regard to critical issues identified in the previous review and identifies new issues as they become apparent from the new literature.

1.1 Summary of the Previous Review

Doebling, et al., [2,3] provides one of the most comprehensive reviews of the technical literature concerning the detection, location, and characterization of structural damage via techniques that examine changes in measured structural vibration response. Issues that were identified include the dependence of many methods on prior analytical models for the detection and location of damage. Also, almost all of the damage-identification methods reviewed on some type of a linear structural model. The number and location of sensors was another important issue that was not addressed to any significant extent in the previously reviewed literature. An issue that was a point of controversy among many researchers was the general level of sensitivity that modal parameters have to small flaws in a structure. A related issue was the discernment of changes in the modal properties resulting from damage from those caused by natural variations in the measurements. The literature was also found to have scarce instances of studies where different health-monitoring procedures were compared directly through application to common data sets. Additionally, research appeared not to be focused more on testing of real structures in their operating environment, but rather on laboratory tests of simple structural systems in controlled environments.

1.2 The Structural Health Monitoring Process

The process of implementing a damage detection strategy for aerospace, civil and mechanical engineering infrastructure is referred to as *Structural Health Monitoring (SHM)*.
The authors believe that the SHM problem is fundamentally one of statistical pattern recognition. Therefore, the damage detection studies reviewed herein are summarized in the context of a statistical pattern recognition paradigm [4]. This paradigm can be described as a four-part process: (1) Operational Evaluation, (2) Data Acquisition, Fusion and Cleansing, (3) Feature Extraction and Information Condensation, and (4) Statistical Model Development for Feature Discrimination.

2. OPERATIONAL EVALUATION

Operational evaluation answers four questions regarding the implementation of a structural health monitoring system: 1)How is damage defined for the system being monitored? 2) What are the conditions, both operational and environmental, under which the system to be monitored

functions? 3) What are limitations on acquiring data in the operational environment? 4)What are teconomic and/or life safety motives for performing the monitoring?
Cawley [5] not only specifies the type of damage, but also he quantifies the extent of detectable damage in terms of the pipe diameter and wall thickness. Staszewski, et al. [6] demonstrate that temperature and ambient vibrations can affect the performance of piezoelectric sensors employed in composite plate tests. Bartelds [7] provides an example of a study where economic and life safety issues have been addressed. He states that the direct costs of carrying out preventive inspections and the indirect costs associated with interrupted service provide a strong stimulus for developing a SHM system for aircraft.

In summary, few of the studies examined in this review address the operational evaluation portion of the SHM paradigm because these studies are focused on laboratory tests. For such tests the damage is prescribed and there is little or no operational or environmental variability. These studies are done as part of research efforts so there is little attention paid to economical and/or life safety justifications for the monitoring system. However, the authors feel that these issues must be addressed if SHM is to make the transition from a research topic to useful systems deployed in the field.

3. DATA ACQUISITION, FUSION AND CLEANSING

The data acquisition portion of the structural health monitoring process involves selecting the types of sensors to be used, the locations where the sensors should be placed, the number of sensors to be used, and the data acquisition/storage/transmittal hardware. Another consideration is how often the data should be collected. There are a large number of studies reporting the development of new sensors and sensing systems for SHM applications. In particular there are significantly more studies on the use of fiber optic sensors (e.g. [8]), MEMS sensors (e.g. [9]), and wireless data acquisitions system (e.g. [10]) appearing in this SHM literature relative to the previous review.

Because data can be measured under varying conditions, the ability to normalize the data becomes very important to the SHM process. One of the most common procedures is to normalize the measured responses by the measured inputs. Sohn, et al. [11] summarizes a procedure for such normalization when direct measures of the varying input are not available. When environmental or operating condition variability is an issue, the need can arise to normalize the data in some temporal fashion to facilitate the comparison of data measured at similar times of an environmental or operational cycle. As an example, Doebling and Farrar [12] measured the temperature differential across the deck of a bridge at 2 hr increments during a 24 hr cycle and correlate these measurements with the change in the bridge’s natural frequencies.

The purpose of data fusion is to integrate data from a multitude of sensors to make a more confident damage detection decision than is possible with any one sensor alone. In many cases data fusion is performed in an unsophisticated manner such as when one examines relative information between various sensors to obtain mode shapes. At other times complex analyses of information from sensor arrays such as those provided by artificial neural networks [13], are used in the data fusion process. Data cleansing is the process of selectively choosing data to accept for, or reject from, the feature selection process. Filtering and decimation are two common data cleansing procedures applied to data acquired during dynamic tests. These techniques are used extensively in the reviewed literature although they are not generally identified by the term "data cleansing".

4. FEATURE EXTRACTION AND INFORMATION COMDENSATION

The area of the SHM that receives the most attention in the technical literature, both in the current and previous review, is feature extraction. Feature extraction is the process of the identifying damage-sensitive properties, derived from the measured system response, which allows one to distinguish between the undamaged and damaged structure. In the current and previous reviews linear modal properties (resonant frequencies, mode shapes, or properties derived from mode shapes such a flexibility coefficients) are the most common features used for damage detection

The current review shows that more investigators are using features that are associated with the systems transition from a predominantly linear, time-invariant system to a system exhibiting nonlinear and time varying response as a result of damage (e.g. [14, 15]).

The implementation and diagnostic measurement technologies needed to perform SHM typically produce a large amount of data. Almost all feature extraction procedures inherently perform some form of data compression. Data compression into feature vectors of small dimension is necessary if accurate estimates of the feature's statistical distribution are to be obtained. As an example, the use of residual errors between auto-regressive model predictions and actual measured time histories represents a one-dimensional feature vector that has been used for damage detection [11]. Note that the data fusion process previously discussed can also be thought of a form of information condensation.

5. STATISTICAL MODEL DEVELOPMENT

The portion of the structural health monitoring process that has received the least attention in the current and previous review is the development of statistical models to enhance the SHM process. Almost none of the hundreds of studies summarized in [2, 3] make use of any statistical methods to assess if the changes in the selected features used to identify damaged systems are statistically significant. The algorithms used in statistical model development usually fall into three categories. When data are available from both the undamaged and damaged structure, the statistical pattern recognition algorithms fall into the general classification referred to as *supervised learning*. *Group classification* and *regression analysis* are supervised learning algorithms. *Unsupervised learning* refers to class of algorithms that are applied to data not containing examples from the damaged structure. In general, some form of *outlier analysis* must be applied for unsupervised SHM.

Supervised learning methods reported in the literature include response surface analysis, linear discriminants, neural networks and genetic algorithms. Unsupervised learning methods include control chart analysis and novelty detection methods.

6. APPLICATIONS

The types of structures that have been the focus of the newly reviewed SHM studies include aircraft, civil infrastructure such as bridges and building, and laboratory specimens like beams and composite plates.

7. SUMMARY

Many damage detection methods reviewed attempt to identify damage by solving an inverse problem, which inevitably requires the construction of analytical models. This dependency on a prior analytical model, which is often uncertain and not fully validated with experimental data, makes these approaches less attractive for certain applications. This issue was already identified in the previous review. Some researcher try to avoid this dependency on the numerical models by performing signal based unsupervised learning. These approaches include novelty/outlier analysis, statistical process control charts, and simple hypothesis testing. These approaches are shown to be very effective for identifying the onset of damage, and they are identified as one of the most significant improvements since the previous literature review, but these approaches only identify the existence of damage.

Another way of solving the inverse problem is the employment of neural network approaches. A neural network can be employed to map the inverse relationship between the measured responses and the structural parameters of interest. However, almost all of the reviewed neural network based approaches suffer from a single common drawback that the training requires a large data sets from both the undamaged and damaged structures and such data are rarely available from real world structures.

One of the main obstacles for deploying a monitoring system in field is the environmental and operations variation of the structure. Although many damage detection techniques are successfully applied to scaled models or specimen tests in controlled laboratory environments, the performance of these techniques in real operational environments is still questionable and needs to be validated. Often the so called damage sensitive features employed in these damage detection techniques are also sensitive to changes of environmental and operation conditions of the structure.

Finally, an area still requiring more work is statistical model development. Compared to the previous review, more studies have some sort of statistical approaches in their damage decision-making process. It should be noted that one is most likely interested in the tails of the distribution for damage detection applications because anomalies from the rest of the population are related damage occurrence. Recent work is underway in Los Alamos to establish damage decision criteria parameterizing the maximum and minimum values of the feature distribution using Extreme Value Statistics.

The updated review will be available at www.lanl.gov/projects/damage_id by August, 2002.

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