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A STATISTICAL PATTERN RECOGNITION PARADIGM FOR VIBRATION-BASED STRUCTURAL HEALTH MONITORING

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ABSTRACT

The process of implementing a damage detection strategy for aerospace, civil and mechanical engineering systems is often referred to as *structural health monitoring*. Vibration-based damage detection is a tool that is receiving considerable attention from the research community for such monitoring. In this paper, the structural health monitoring problem is cast in the context of a statistical pattern recognition paradigm. This pattern recognition process is composed of four portions; (1) operational evaluation, (2) data acquisition & cleansing, (3) feature selection & data compression, and (4) statistical model development. A general discussion of each portion of the process is presented, and the application of this statistical paradigm to two different real world structures, such as a bridge column and a surface-effect fast boat, is studied focusing on the issues of data normalization and feature extraction.

INTRODUCTION

Many aerospace, civil, and mechanical engineering systems continue to be used despite aging and the associated potential for damage accumulation. Therefore, the ability to monitor the structural health of these systems is becoming increasingly important from both economic and life-safety viewpoints. Damage identification based upon changes in dynamic response is one of the few methods that monitor changes in the structure on a global basis. The basic premise of vibration-based damage detection is that damage will significantly alter the stiffness, mass or energy dissipation properties of a system, which, in turn, alter the measured dynamic response of that system. Although the basis for vibration-based damage detection appears intuitive, its actual application poses many significant technical challenges. Because all vibration-based damage detection processes rely on experimental data with inherent uncertainties, statistical analysis procedures are necessary if one is to state in a quantifiable manner that changes in the vibration response of a structure are indicative of damage as opposed to operational and/or environmental variability. Therefore, this paper poses the vibration-based damage detection process in the context of a problem in statistical pattern recognition.

A STATISTICAL PATTERN RECOGNITION PARADIGM

In the context of statistical pattern recognition the process of vibration-based damage detection can be broken down into four parts; (1) operational evaluation, (2) data acquisition & cleansing, (3) feature extraction & data compression, and (4) statistical model development.

Operational evaluation answers four questions in the implementation of a structural health monitoring system; (1) What are the life safety and/or economic justifications for monitoring the structure?; (2) How is damage defined for the system being monitored?; (3) What are the operational and environmental conditions under which the system of interest functions?; and (4) What are the limitations on acquiring data in the operational environment? Operational evaluation begins to set the limitations on what will be monitored and how to perform the monitoring as well as tailoring the monitoring to unique aspects of the system and unique features of the damage that is to be detected.

The *data acquisition* portion of the structural health monitoring process involves selecting the types of sensors to be used, the location where the sensors should be placed, the number of sensors to be used, and the data acquisition/storage/transmittal hardware. Other considerations that must be addressed include how often the data should be collected, how to normalize the data, and how to quantify the variability in the measurement process. *Data cleansing* is the process of selectively choosing data to accept for, or reject from, the feature selection process. Filtering is one of the most common methods for data cleansing.

The area of the structural damage detection process that receives the most attention in the technical literature is *feature extraction*. Feature extraction is the process of the identifying damage-sensitive properties derived from the measured vibration response that allows one to distinguish between the undamaged and damaged structures. Doebling et al. (1998) review propose many different methods for extracting damage-sensitive features from vibration response measurements. However, few of the cited references take a statistical approach to quantifying the observed changes in these features. The diagnostic measurement needed to perform structural health monitoring typically produces a large amount of data. *Data compression* into small dimensional features is necessary if accurate estimates of the feature statistical distribution are to be obtained. The need for low dimensionality in the feature vectors is referred to as the "curse of dimensionality" and is discussed in detail in general texts on statistical pattern recognition (Bishop 1995).

The portion of the structural health monitoring process that has received the least attention in the technical literature is the development of statistical models to enhance the damage detection process. *Statistical model development* is concerned with the implementation of the algorithms that analyze the distributions of the extracted features in an effort to determine the damage state of the structure. The algorithms used in statistical model development usually fall into the three general categories of; (1) group classification, (2) regression analysis, and (3) outlier detection. The appropriate algorithm to use will depend on the ability to perform *supervised* or *unsupervised* learning. Here, supervised learning refers to the case were examples of data from damaged and undamaged structures are available. Unsupervised learning refers to the case were data are only available from the undamaged structure.

EXPERIMENTAL APPLICATIONS

The statistical pattern recognition paradigm is applied to vibration test data obtained from two different structural systems; (1) acceleration time series obtained from a pier in its undamaged state and then after various levels of damaged had been introduced through cyclic loading, and (2) strain time measurements recorded under various operational and environmental conditions of a surface-effect fast patrol boat. The examples presented here emphasize on the issues of data normalization and feature extraction.

A Bridge Column Test

This test applies statistical process control methods referred to as "control charts" to vibration-based damage detection (Montgomery, 1996). In this study an X-bar control chart is employed to monitor the changes of the selected feature means and to identify samples that are inconsistent with the past data sets. Application of the S control chart, which measures the variability of the structure over time, to the current test structure is presented in Fugate et al (2000). First, an auto-regressive (AR) model is fit to the measured acceleration-time histories from an undamaged structure. Residual errors, which quantify the difference between the prediction from the AR model and the actual measured time history at each time interval, are used as the damage-sensitive features. (Note that correlated data lead to the underestimation of control limits. The use of residual errors as damage sensitive features removes correlation in the data being monitored by the control charts.) Next, the X-bar and S control charts are employed to monitor the mean and variance of the selected features. Control limits for the control charts are constructed based on the features obtained from the initial intact structure. The residual errors computed from the previous AR model and subsequent new data are then monitored relative to the control limits. A statistically significant number of error terms outside the control limits indicate a system transit from a healthy state to a damage state. The assumption here is that there will be a significant increase in the residual errors when an AR model developed from the undamaged linear system response is used to predict the response from a damaged system exhibiting nonlinear response. For demonstration, this statistical process control is applied to vibration test data acquired from a concrete bridge column (Figure 1) as the column is progressively damaged. The details of the test structure are given in Fugate et al (2000)

Figure 2 shows the control charts for all damage levels. In these charts, CL, UCL, and LCL denote the centerline, upper and lower control limits, respectively. Outliers correspond to subgroup sample means outside the control limits and are marked by a "+". Because the control limits represent a 99% confidence interval, approximately 20 charted values (= 1 % of total 2046 samples) are expected to be outside the control limits even when the system is in control. Therefore, the 13 outliers in Figure 2 (a) are not unusual and do not indicate any system anomaly for damage level 0. However, the control charts successfully indicated some system anomaly for damage levels 1 though 5 by showing a statistically significant number of outliers.

In general, the observation of a large number of outliers does not necessarily indicate that a structure is damaged but only that the system has varied to cause statistically significant changes in its vibration signature. This variability could be caused by a variety of environmental and operational conditions that the system of interest is subject to. A data normalization procedure to account for these operational and environmental variations is presented in the next example.

A Surface-Effect Fast Patrol Boat

This example discusses on the data normalization issue using the fiber optic strain gauge data obtained from different structural conditions of a surface-effect fast patrol boat (Figure 3). Three strain time-histories obtained from two different structural conditions were transmitted to the staff at Los Alamos National Laboratory (LANL) from Naval Research Laboratory (NRL). The actual measurement and data acquisition were undertaken by the staff at NRL. It was explained that the first two signals, Signal 1 and Signal 2, hereafter, were measured when the ship was in "Structural Condition 1" while Signal 3 was measured when the ship was in "Structural Condition 2". It is assumed that these data were acquired under varying environmental and operational conditions. Changing environmental conditions can include varying sea states and thermal environments associated with the water and air. Changing operational conditions include ship speed and the corresponding changes in engine performance, mass associated with varying ship cargo, ice buildup and fuel levels, and maneuvers the ship undergoes. No measures of these environmental or operational conditions were provided. The details of this example are summarized in Sohn et al., 2000.

The goal of this investigation is to normalize these data and extract the appropriate features such that we could clearly discriminate Signal 3 from Signals 1 and 2. Also, we must be able to show that the same procedure does not discriminate Signal 1 from Signal 2. Various signal analyses have been conducted to achieve this objective. The conclusion from these analyses was that environmental conditions such as sea states or operational conditions such as the boat speed were making it impossible to distinguish between the two structural states.

To overcome this difficulty, a novel data normalization procedure is proposed in this study. Here, we utilize the additional information that Signals 1 and 2 are obtained from the same structural condition of the system. That is, a supervised learning mode is adopted here while the previous approaches are conducted in an unsupervised learning mode. We first divide each signal into two parts. The first halves of Signals 1 and 2 are employed to generate the "reference database". The second halves of Signals 1 and 2 are later employed for false-positive studies. Signal "blocks" in the reference database are generated by further dividing the first halves of Signals 1 and 2 into smaller segments. These reference signals are considered to be "the pool" of signals acquired from the various operational conditions, but a known structural condition of the system. (In our case, we assume that Signals 1 and 2 are measured under different operational conditions of the surface-effect fast patrol boat. However, it is also known that these two signals correspond to the same structural condition of the system.) When a new signal is recorded (for example, when Signal 3 is measured in our case), we divide the signal into smaller segments, as done for the blocks in the reference database, and we look up the reference database and find a signal block "closest" to a new signal block. The matrix, which is defined as the distance measure of two separate signal segments, is subjective. The matrix formulation used in this study is described in Sohn et al., 2000.

This approach is based on the premise that if the new signal block is obtained from the same operation condition as one of the reference signal segments and there has been no structural deterioration or damage to the system, the dynamic characteristics of the new signal should be similar to those of the reference signal based on some measure of "similarity". That is, if we construct an auto-regressive model with exogenous inputs (ARX) as our time prediction model from the selected reference waveform, this prediction model also should work for the new signal if the signal is "close" to the original. For example, if the second half of Signal 1 is assumed to be our new blind-test signal, the prediction model obtained from the first half of Signal 1 should reproduce the new signal (the second half of Signal 1) reasonably well. On the other hand, because Signal 3 is measured under the different structural condition of the system, the prediction model obtained from either Signal 1 or Signal 2 would not predict Signal 3 well even if a "similar" waveform were analyzed. Therefore, we define the ratio of the standard deviations of the residual errors, $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$, as our damage-sensitive feature. Here, $\sigma(\varepsilon_x)$ is the standard deviation of the residual errors obtained by fitting a ARX model to the closest reference signal, and $\sigma(\varepsilon_y)$ is the counterpart of $\sigma(\varepsilon_x)$ obtained by fitting the same ARX model to the new signal.

The classification tests of two structural conditions are conducted by randomly drawing testing signal blocks from Signals 1, 2 and 3. For the first 40 classification tests, the first halves of Signals 1 and 2 are used as the reference signals, and the second halves of Signals 1 and 2 are used as the reference signals for the next 40 classification tests. To summarize, 20 testing blocks are sampled from either the first or second half of Signal 1 depending on which portion of Signal 1 is used as part of the reference database. In a similar way, 20 blocks are drawn from Signal 2. Additional 40 blocks are collected from Signal 3 (20 from the first half and another 20 from the second half).

The $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ ratios for these testing blocks are shown in Figure 4. Separation of Signal 3 from Signals 1 and 2 is attempted by setting the threshold value to be 1.85 (h=1.85). This threshold value results in only 4 misclassifications out of 80 tested cases. That is, 95% of the tested blocks are correctly assigned to their structural conditions. That is, we were able to show that Signal 3 is somehow different from either Signal 1 or Signal 2 employing the additional information that Signals 1 and 2 are obtained from the same structural condition. The same procedure also shows that Signals 1 and 2 are similar. Note that the threshold value employed here is established rather in an *ad hoc* manner. When more test data become available, the threshold value should be established based on a more rigorous statistical approach.

SUMMARY

A vibration-based damage detection problem is cast in the context of statistical pattern recognition. A paradigm of statistical pattern recognition is described in four parts: operational evaluation, data acquisition & cleansing, data reduction & feature extraction, and statistical modeling for discrimination. This study has focused on the issues of data normalization, feature extraction, and statistical model development. Two different experimental test results are briefly discussed. For the second example, three strain measurements obtained from a surface-effect fast patrol boat were studied. The structural condition was the same when Signals 1 and 2 were obtained but Signal 3 was recorded in a different structural condition than when Signals 1 and 2 were obtained.

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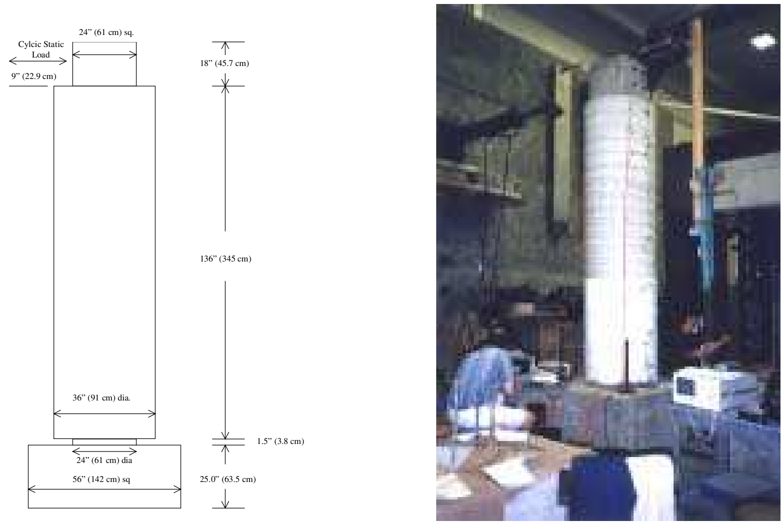

Figure 1: Column dimensions and photo of an actual test structure

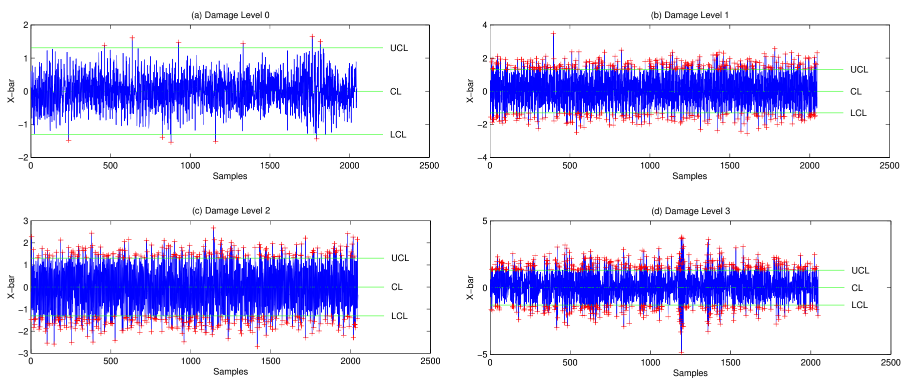

Figure 2: X-bar control chart of the residual errors

Figure 3: Surface-effect fast patrol boat

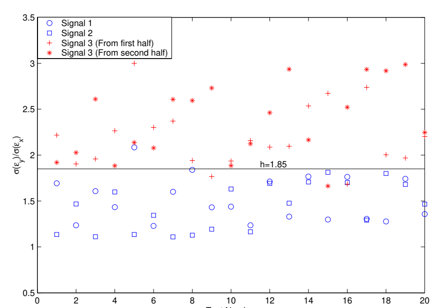

Figure 4: Separation of Signal 3 from Signals 1 and 2 using the ARX residual errors