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ABSTRACT

Structural health monitoring (SHM) is the implementation of a damage detection strategy for aerospace, civil and mechanical engineering infrastructure. Typical damage experienced by this infrastructure might be the development of fatigue cracks, degradation of structural connections, or bearing wear in rotating machinery. For SHM strategies that rely on vibration response measurements, the ability to normalize the measured data with respect to varying operational and environmental conditions is essential if one is to avoid false-positive indications of damage. Examples of common normalization procedure include normalizing the response measurements by the measured inputs as is commonly done when extracting modal parameters. When environmental cycles influence the measured data, a temporal normalization scheme may be employed. This paper will summarize various strategies for performing this data normalization task. These strategies fall into two general classes: 1. Those employed when measures of the varying environmental and operational parameters are available; 2. Those employed when such measures are not available. Whenever data normalization is performed, one runs the risk that the damage sensitive features to be extracted from the data will be obscured by the data normalization procedure. This paper will summarize several normalization procedures that have been employed by the authors and issues that have arose when trying to implement them on experimental and numerical data.

INTRODUCTION

The process of implementing a damage detection strategy for aerospace, civil and mechanical engineering infrastructure is referred to as *structural health monitoring (SHM)*. Here *damage* is defined as changes to the material and/or geometric properties of these systems, including changes to the boundary conditions

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and system connectivity, which adversely affect the system's performance. The SHM process involves the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors, the extraction of damage-sensitive features from these measurements, and the statistical analysis of these features to determine the current state of system health. For long term SHM, the output of this process is periodically updated information regarding the ability of the structure to perform its intended function in light of the inevitable aging and degradation resulting from operational environments. After extreme events, such as earthquakes or blast loading, SHM is used for rapid condition screening and aims to provide, in near real time, reliable information regarding the integrity of the structure.

The authors believe that the SHM problem is best addressed as a problem in statistical pattern recognition. In this context, the SHM process can be broken down into four parts: (1) Operational Evaluation, (2) Data Acquisition and Cleansing, (3) Feature Extraction and Data Compression, and (4) Statistical Model Development [1]. Texts are available that provide a good general overview of statistical pattern recognition technology [2].

Operational evaluation answers four questions regarding the implementation of a SHM system: 1. What are the economic and/or life safety motives for performing the monitoring? 2. How is damage defined for the structure that will be monitored? 3. What are the conditions, both operational and environmental, under which the system to be monitored functions? and 4. What are the limitations on acquiring data? Operational evaluation begins to tailor the process to unique aspects of the monitored system and unique features of that system's damage.

Data acquisition involves selecting the types, number and location of sensors to be used, and the data acquisition/storage/transmittal hardware. Other considerations 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 operations, such as filtering and decimation, are used to selectively eliminating some of the measured data before the feature extraction process.

The area of the SHM 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 system response, which allows one to distinguish between the undamaged and damaged structure. Data compression is inherently part of most feature extraction procedures. A relatively recent review of the features for SHM is summarized in [3].

Statistical model development is concerned with the implementation of the algorithms that analyze the distribution of extracted features in an effort to determine the damage state of the structure. The algorithms used in statistical model development fall into the three general categories: 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 is only available from the undamaged structure.

For SHM strategies that rely on vibration response measurements, robust data normalization procedures are necessary if this technology is to mature from laboratory demonstration problems to field implementation on complex aerospace, civil and mechanical engineering infrastructure. Without such data normalization procedures, varying operational and environmental conditions will produce false-positive indications of damage and quickly erode confidence in such SHM procedures. The challenge presented for the development of data normalization procedures is illustrated in Figure 1. Here, three strain time histories have been measured on the composite hull of a surface-effects fast patrol boat [4]. The first two signals correspond to a similar system condition while the third signal corresponds to an alternate system condition. These recordings were made when the boat was operating in different sea states. Clearly, the varying sea states have a significant influence on the recorded data. This influence must me removed if one is to determine that the changing system condition can be detected from changes in the measured vibration response.

These approaches to data normalization fall into two general categories: 1. Cases when the source of variability can be measured, and 2. Cases when the sources of variability cannot be measured. Figure 2 illustrates the case when it is necessary to have a measure of the variability source. In Figure 2 the change in the distribution of damage sensitive features caused by some source of variability

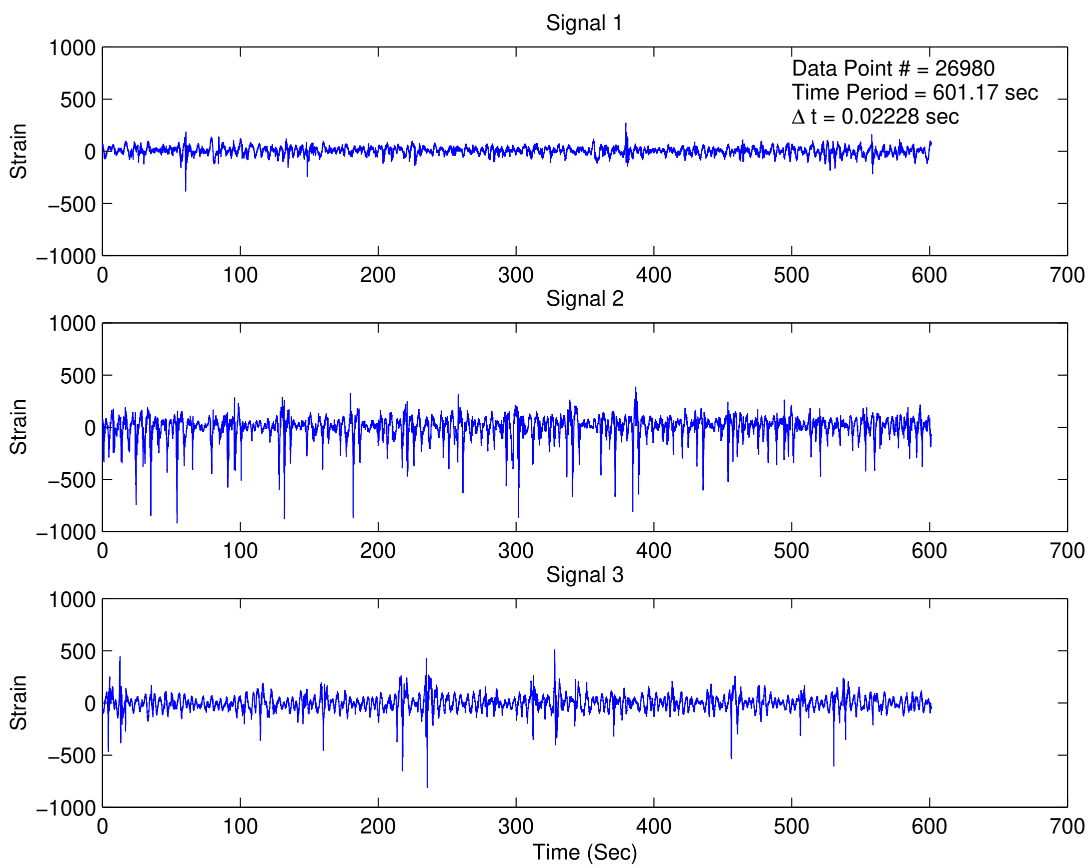

FIGURE 1 THREE STRAIN-TIME HISTORIES RECORDED ON THE HULL OF SURFACE EFFECTS FAST PATROL BOAT DURING VARYING SEA STATES.

produces changes similar to those caused by damage. For this case a measure of the variability source will, most likely, be necessary. In Figure 3 damage produces a change in the feature distribution that is in someway orthogonal to the change caused by the environmental or operational variability. In this case it may be possible to distinguish changes in the feature distribution caused by damage from the changes caused by the sources of variability without a measure of the operational or environmental variability.

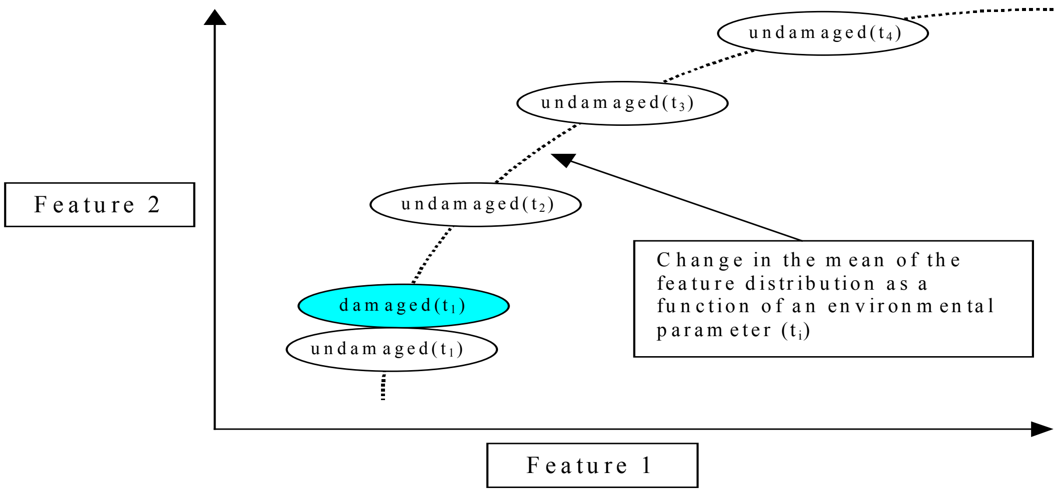

FIGURE 2 A HYPOTHETICAL CASE WHERE DAMAGE PRODUCES A CHANGE IN THE FEATURE DISTRIBUTION THAT IS SIMILAR TO THE CHANGE CAUSED BY THE ENVIRONMENTAL VARIABILITY.

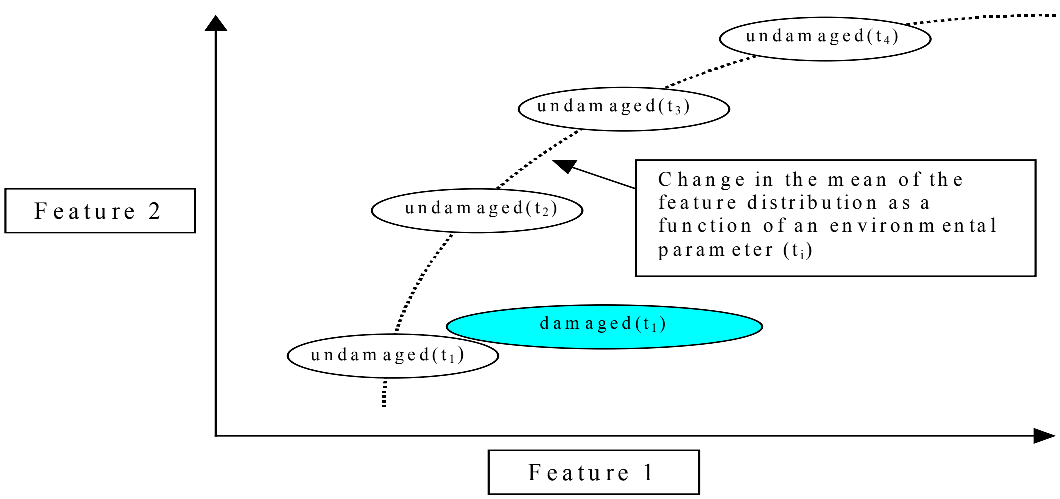

FIGURE 3 A HYPOTHETICAL CASE WHERE DAMAGE PRODUCES A CHANGE IN THE FEATURE DISTRIBUTION THAT IS IN SOME MANNER ORTHOGONAL TO CHANGES CAUSED BY THE ENVIRONMENTAL VARIABILITY.

Successful damage detection methodologies will be required to perform accurately when the structure is subjected to varying environmental and operational conditions. As an example, a bridge will be subject to varying thermal environments that will change on a daily and on a seasonal cycle. For longer suspension and cable-stayed bridges wind can significantly influence the measured vibration response. Rain can be absorbed by the bridge deck and change the mass of the structure as well as the soil properties at the piers and abutments. Operational variability for a bridge is primarily associated with traffic flow. The measured vibration response will change significantly based on the volume of traffic and the speed of that traffic. Traffic flow can vary on daily basis, between the work week and weekend, and the flow can vary as a result of unique and unpredictable events such as a traffic accident. Analogous environmental and operational variability scenarios can be defined for aerospace and mechanical engineering systems. All of these applications necessitate the development of robust data normalization procedures that can be used to minimize the uncertainty in damage state assessments when those assessments are made in the presence of environmental and operational variability.

Some data normalization procedures that have been studied by the authors will now be summarized. These normalization procedures must be applied with care because the procedure can attenuate the system's damage-sensitive features.

DATA NORMALIZATION PROCEDURES

There are many data normalization procedures that are commonly employed with measured vibration data. The mean value of a measured time history is often subtracted from that signal to remove DC offsets from the signal. Division by the standard deviation of the signal is done to normalize for varying amplitudes in the signal. Experimental modal analysis procedures involve curve fitting analytical forms of the frequency response function to measured frequency response functions. These frequency response functions are formed by normalizing the measured response by the measured input. If the structure is linear, this normalization procedure removes the influence of the input from the parameter estimation procedure.

Identification and Quantification of Source of Variability

Clearly, in any structural health monitoring application it is most desirable to directly measure all sources of variability that can influence the features extracted from the measured data that are being used discriminate between and healthy and damaged system. However, the sensors and data acquisition hardware needed to make such measurements will increase the cost of the deployed system. Also, it is often difficult to define *a priori* all the sources of operational and environmental variability that will influence the selected features.

Normalization Procedures When Source of Variability can be Quantified

A general approach to data normalization for structural health monitoring applications include measuring the response of the healthy structure over a period of time while recording various measures of the operational and environmental variability. The damage sensitive data features associated with the healthy system can then be defined as a function or the measured operational and environmental parameters. When new system response data becomes available along with new measures of the operational and environmental conditions, the features extracted from these data can be compared to features extracted form data measured on the healthy structure under similar conditions. The authors refer to this data normalization procedure as developing a “reference database” of environmental and operation conditions.

Normalization Procedures When Source of Variability cannot be Quantified

AUTO-ASSOCIATIVE NEURAL NETWORKS

One approach investigated by the authors for the case when measures of the variability source are not available is based on auto-associative neural networks where target outputs are simply inputs to the network. Using the measured features corresponding to the normal conditions, the auto-associative neural network is trained to characterize the underlying dependency of the measured features on the unmeasured environmental and operational variations by treating these environmental and operational conditions as hidden intrinsic variables in the neural network [5].

The development of this neural network is based on nonlinear principal component analysis (NLPCA). NLPCA is used as an aid to multivariate data analysis. While principal component analysis (PCA) is restricted on mapping only linear correlations among variables, NLPCA can reveal the nonlinear correlations presented in data. If nonlinear correlations exist among variables in the original data, NLPCA can reproduce the original data with greater accuracy and/or with fewer factors than PCA. This NLPCA can be realized by training a feed-forward neural network to perform the identity mapping, where the network outputs are simply the reproduction of network inputs. For this reason, this special kind of neural network is named as an *auto-associative neural network*. The network consists of an internal “bottleneck” layer and two additional hidden layers. The bottleneck layer contains fewer nodes than input or output layers forcing the network to develop a compact representation of the input data. The NLPCA presented in this paper is a general purpose feature extraction/data reduction algorithm discovering features that contain the maximum amount of information from the original data set.

NLPCA generalizes the linear PCA mapping by allowing arbitrary nonlinear functionalities. NLPCA seeks a mapping in the following form:

$$\mathbf{X} = \mathbf{G}(\mathbf{Y}) \tag{1}$$

where **G** is a nonlinear vector function and consists of d number of individual nonlinear functions: **G** = $\{G_1, G_2, \ldots, G_d\}$. The inverse transformation, restoring the original dimensionality of the data, is implemented by a second nonlinear vector function **H**:

$$\hat{\mathbf{Y}} = \mathbf{H}(\mathbf{X}) \tag{2}$$

The information lost is measured by **E**= $\mathbf{Y} - \hat{\mathbf{Y}}$. Similar to PCA, **G** and **H** are computed to minimize the Euclidean norm of ||**E**|| meaning minimum information loss in the same sense as PCA. NLPCA employs artificial neural networks to generate arbitrary nonlinear functions. It has been shown that functions of the following form are capable of fitting any nonlinear function $\mathbf{y} = f(\mathbf{x})$ to an arbitrary degree of precision:

$$y_k = \sum_{j=1}^{N_2} w_{jk}^2 \sigma\left(\sum_{i=1}^{N_1} w_{ij}^1 x_i + b_j \right) \tag{3}$$

where y_k and x_i are the kth and ith components of **y** and **x**, respectively. w_{ij}^k represents the weight connecting the ith node in the kth layer to the jth node in the *(k+1)*th layer, and b_j is a node bias. $\sigma(x)$ is a monotonically increasing continuous function with the output range of 0 to 1 for an arbitrary input x. A sigmoid transfer function is often used in neural networks to realize this function.

Note that, to fit arbitrary nonlinear functions, at least two layers of weighted connections are required, and the first hidden layer should be composed of sigmoidal functions. Therefore, the two nonlinear vector functions in Equations 1 and 2 should have the same architecture: one hidden layer with sigmoidal functions and one output layer. The output layer can have either linear or sigmoidal transfer functions without affecting the generality of the mapping. For instance, the first hidden layer of **G**, which consists of M_1 nodes with sigmoidal functions, operates on the columns of **Y** mapping m inputs to M_1 node outputs. The output of the first hidden layer is projected into the bottleneck layer, which contains d nodes. In a similar fashion, the inverse mapping function **H** takes the columns of X as inputs relating d inputs to M_2 node outputs. The final output layer reconstructs the target output $\hat{\mathbf{Y}}$, and contains m nodes.

It should be noted that if the neural networks for **G** and **H** are to be trained separately, the target output **X** is unknown for the training of the **G** network. For the same reason, the input for the **H** network is not known. It is observed that X is both the output of **G** and the input of **H**. Therefore, combining the two networks in series, where G feed directly into H, results in a new network whose inputs and target outputs are not only known but also identical. Now, supervised training can be applied to the combined network.

The combined network contains three hidden layers; the mapping, the bottleneck, and de-mapping layers. The second hidden layer is referred to as the *bottleneck layer* because it has the smallest dimension among the three layers. Note that the nodes in the mapping and de-mapping layers must have nonlinear transfer functions to model arbitrary **G** and **H** functions. However, nonlinear transfer functions are not necessary in the bottleneck layer. If the mapping and de-mapping layers were eliminated and only the linear bottleneck layer were left, this network would reduce to linear PCA. Typically M_1 and M_2 are selected to be larger than m and they are set to be equal ($M_1 = M_2$).

In the study reported in [5], the auto-associative network is employed to reveal the latent relationship between the measured features and the unmeasured intrinsic parameters causing the variations of the measured features. The auto-associative neural network presented here can be trained to learn these correlations and reveal the inherent variables driving the changes. Then, assuming that the neural network is trained to capture the embedded relationships, the prediction error of the neural network will grow when an irrelevant data set, such as ones obtained from a damage state of the system, is fed to the network. Based on this assumption, the auto-associate network is incorporated with novelty detection, which is described in [5] where it is applied to a numerical simulation of a damaged disk drive subjected to a changing thermal environment. A drawback of this approach is that one needs to make an assumption regarding the size of the bottleneck layer, which is related to the number of unmeasured operational and environmental parameters that influence the features extracted from the measured data.

REFERENCE DATABASE APPROACH

The authors have also employed a reference database for analyzing the data from the surface effects fast patrol boat (Figure 1) when no measures of the operational and environmental variability were available [4, 6]. As can be observed in Figure 1, there is a noticeable difference between Signals 1 and 2 because of operational variation of the boat. It seems extremely difficult to group Signals 1 and 2 together, and at the same time separate Signal 3 from them. The data normalization procedure for this case begins by assuming that a "pool" of signals is acquired from various unknown operational and environmental conditions, but from a known structural condition of the system. The ability of this procedure to normalize the data will be directly dependent on this pool being representative of data measured in as many varying environmental and operational conditions as possible. The collection of these time series is called "the reference database" in this study.

For this particular example at hand, each signal is first divided into two parts. The first halves of Signal 1 and Signal 2 are employed to generate the "reference database". The second halves of Signal 1 and Signal 2 are later employed for false-positive studies. In this example, signal "blocks" in the reference database are generated by further dividing the first halves of Signal 1 and Signal 2 into smaller segments. These reference signals are considered to be "the pool" of signals acquired from the various operational conditions, but from a known structural condition of the system. (In this example, Signals 1 and 2 are assumed to have been 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), this signal is divided into smaller segments, as done for the blocks in the reference database. Then, the signals in the reference database are examined to find a signal block "closest" to the new signal block, and the selected signal is designated a "reference signal". Here, the metric, which is defined as the distance measure of two separate signal segments, is subjective. The detailed formulation of the metric used in this study and the definition of the "closeness" is described in [4, 6].

Second, a two-stage prediction model, combining Auto-Regressive (AR) and Auto-Regressive with eXogenous inputs (ARX) techniques, is constructed from the selected reference signal. Then, the residual error, which is the difference between the actual acceleration measurement for the new signal and the prediction obtained from the AR-ARX model developed from the reference signal, is defined as the damage-sensitive feature.

This approach is based on the premise that if the new signal block is obtained from the same operational condition as one of the reference signal segments and there has been no structural deterioration or change 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 a time prediction model, such as AR-ARX model employed here, is constructed 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 a 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, if the new signal is recorded under a structural condition different from the conditions where reference signals are obtained, the prediction model estimated from even the "closest" waveform in the reference database should not predict the new signal well. For instance, 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 "similar" waveforms were analyzed. Therefore, the residual errors of the "similar" signals are defined as the damage-sensitive features, and the change of the probability distribution of these residual errors is monitored to detect system anomaly.

Finally an approach currently being considered by the authors and their colleagues is to deploy a local actuation system that can be used to apply known inputs to the structure at discrete locations and tailored to the structural health monitoring activity. The concept here is that the tailored inputs will outweigh any unmeasured inputs caused by the changing operational and/or environmental conditions.

SUMMARY AND DISCUSSIONS

In this paper the authors have identified the issue of data normalization as a key concern when deploying a structural health monitoring system on a "real-world" structure. The optimal approach to accomplish such data normalization is to obtain a measure of the operational and/or environmental variability that can lead to false-positive indications of damage. However, the instrumentation required for this approach can potentially be costly and considerable time may be required to capture the requisite portions of operational and environmental cycles.

The paper also summarized approaches to the data normalization problem that have been used when measures of the operational and environmental conditions are not available. These methods are effective for the case illustrated in Figure 3 where the damage produces changes to the feature distribution that is in some way orthogonal to the changes produced by the sources of environmental and/or operational variability. However, the authors have not developed a procedure that is appropriate for the case illustrated in Figure 2 where damage produces changes in the feature distribution that is similar to the changes caused by the environmental and operational variability and measured of this variability do not exist. Clearly, there is a need for more studies of the data normalization procedures as they apply to damage detection strategies. Without such procedures it is the authors opinion that structural health monitoring will have a difficulty making the transition from a field of research to actual implementation on "real-world" hardware. It is of interest to note that the most successful applications of structural health monitoring, those associated with machinery condition monitoring, are often accomplished with systems subjected to minimal operational and environmental variability.

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