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Title: DATA NORMALIZATION ISSUE FOR VIBRATION-BASED STRUCTURAL HEALTH MONITORING

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DATA NORMALIZATION ISSUE FOR VIBRATION-BASED STRUCTURAL HEALTH MONITORING

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1. ABSTRACT

The process of implementing a damage detection strategy for aerospace, civil and mechanical engineering systems is often referred to as *structural health 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 for feature classification. This paper mainly focuses on the discussion of feature extraction and classification issues using the fiber optic strain gauge data obtained from two different structural conditions of a surface-effect fast patrol boat. The main objective is to extract features and to construct a statistical model that enables to distinguish the signals recorded under the different structural conditions of the boat. The feature extraction process began by looking at relatively simple statistics of the signals and progressed to using the residual errors from auto-regressive (AR) models fit to the measured data as the damage-sensitive features. Data normalization proved to be the most challenging portion of this investigation. A novel approach to data normalization, where the residual errors in the AR model are considered to be an unmeasured input and an auto-regressive model with exogenous inputs (ARX) is then fit to portions of the data exhibiting similar waveforms, was successfully applied to this problem. With this proposed procedure, a clear distinction between the two different structural conditions was achieved.

2. 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 changes in the physical properties, such as reductions in stiffness resulting from the onset of cracks or loosening of a connection, will cause changes in the measured dynamic response of the structure.

This paper begins by posing the structural health-monitoring problem in the context of a statistical pattern recognition paradigm. This paradigm can be described as a four-part process: 1.) operational evaluation, 2.) data acquisition & cleansing, 3.) feature extraction & data reduction, and 4.) statistical model development. In particular, this paper focuses on Parts 3 and 4 of the process. More detailed discussion of the statistical pattern recognition paradigm can be found in Farrar et al, 2000.

3. DESCRIPTION OF EXPERIMENTAL DATA

Staff at Los Alamos National Laboratory (LANL) applied some of the LANL pattern recognition techniques developed for structural health monitoring to data obtained from a surface-effect fast patrol boat shown in Figure 1. The surface effect ship is a pre-series fast patrol boat built by Kvaerner Mandal in Norway. Together with a research team from the Norwegian Defense Research Establishment (NDRE), the ship designers determined the optimal sensor placement. The sensor installation and data acquisition during sea trials was performed jointly by NDRE and NRL. Fiber optic strain guage with Bragg grating were used to measure the dynamic response of the ship. The boat and the associated data acquisition are summarized in Johnson et al. (2000).

Three strain time-histories obtained from two different structural conditions were transmitted to the staff at Los Alamos National Laboratory (LANL) from 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". However, we were not told which sensor these data came from. We were not informed of any data cleansing or data normalization that was performed prior to the transmission of these signals to LANL. 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.

Given that the first two portions of the statistical pattern recognition paradigm have mostly been completed, this study focused on data normalization, feature extraction, and statistical modeling for feature discrimination. 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. The following section describes the procedures used to obtain these goals.

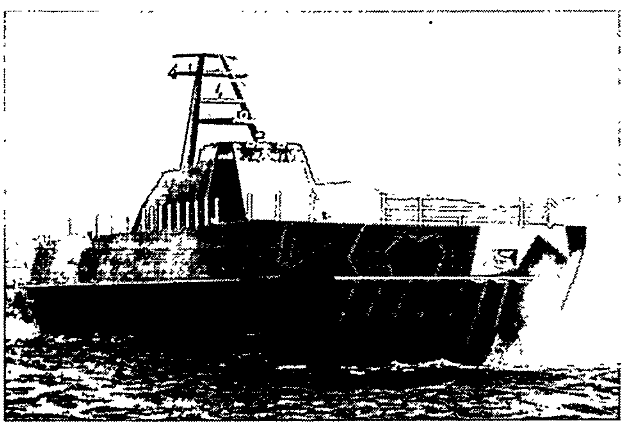

Figure 1: A surface-effect fast patrol boat

4. FEATURE EXTRACTION & CLASSFICATION

4.1 The Raw Time Series

First, the raw time series are plotted in Figure 2 to get some intuitive feeling for the signals. A few observations could be made based on this figure: (1) All the signals have "spiky" responses with an occasional large amplitude strain measurement, (2) the amplitude of one signal is not consistent with the amplitude of the other signals indicating the need for data normalization, and (3) significant "skewness" is found in Signal 2. To support some of these observations, some basic statistics of the raw time series are summarized in Table 1.

Table 1: Basic statistics of the raw time series amplitudes

Series	Mean	STD	Skewness	Kurtosis
Signal 1	3.7809	37.7433	-0.4811	6.0854
Signal 2	-0.8207	107.8089	-2.2310	12.6311
Signal 3	-0.7559	74.1260	-0.8134	11.9437

A close look of Table 1 further reveals important facts regarding the data. The sample mean and standard deviation (STD) of one time series are quite different from those of the others signals. Therefore, it seems necessary to conduct some form of data normalization or standardization prior to any statistical model development.

To achieve our main objective, which is to group Signals 1 and 2 together and to separate Signal 3 from Signals 1 and 2, various signal analyses have been conducted. To name a few, Fast Fourier Transformation (FFT) analysis, Statistical Control Chart Analysis using residual errors obtained from AR models, Probability Density Estimation of the residual errors, Bispectrum & Bicoherence Analysis, and Time-Frequency Analysis using Spectrogram. It was difficult to discern, either qualitatively or quantitatively, any consistent difference between Signals 1 and 2 (Structural Condition 1) and Signal 3 (Structural Condition 2). The visual inspection of some results often shows more similarity between Signals 1 and 3 than between Signals 1 and 2. The conclusion from the aforementioned 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. The details of these analyses are summarized in Sohn et al., 2000.

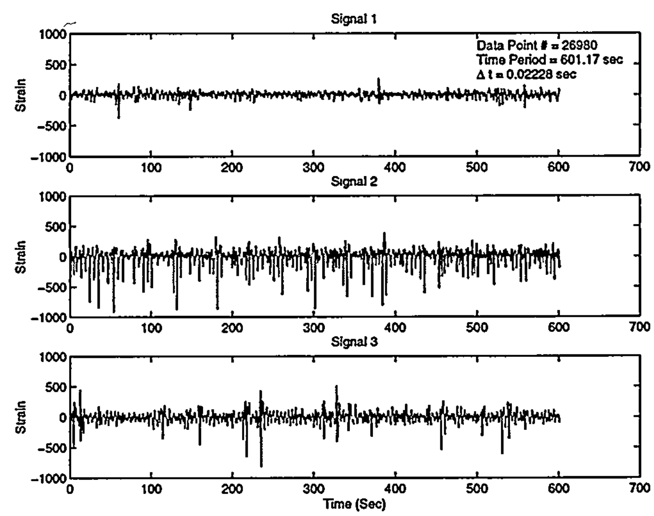

Figure 2: The raw strain time series

4.2 AR-ARX Analysis

As shown in the previous examples, there is a noticeable difference between Signals 1 and 2. It seems extremely difficult to group Signals 1 and 2 together, and at the same time separate Signal 3 from them. Therefore, a different approach is tried. Here, the additional information that Signals 1 and 2 are obtained from the same structural condition of the system is utilized.

We first divide each signal 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 in this example), 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. Here, the matrix, which is defined as the distance measure of two separate signal segments, is subjective. The detailed formulation of the matrix used in this study and the definition of the "closeness" will be described later on.

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 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 a time prediction model, such as AR, Auto-Regressive and Moving-Average (ARMA), or Auto-Regressive models with eXogenous inputs (ARX), 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 are 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.

In general, a linear time prediction model can not capture the dynamic characteristics of nonlinear time series well. To overcome this problem, a "local" modeling approach is employed. Instead of fitting a linear model to the entire time series, the time series is divided into small segments and a linear model is fit into each local region of the time series. That is, although the local prediction model is linear, the parameters of the linear model adapt to the data in each region of the time series. The procedure is described below in detail.

1 We decimate all three signals by a factor of four. This decimation reduces the original sampling rate of the signal, 44.88Hz, to a lower rate, 11.22Hz. The decimation process first filters the signal with an eighth-order lowpass Chebyshev type I filter for better anti-aliasing performance. (The cutoff frequency is set to be $(0.8/R)\times(F_s/2)$. Here, F_s is the original sampling rate, 44.88Hz, and R is the decimation rate, 4.) Then, the decimation process re-samples the resulting filtered signal at the lower rate of 11.22Hz (Oppenheim and Willsky, 1996). Each signal consists of 26980 points with the duration of 601.1667 seconds and resulting in a sampling rate of 44.88Hz (=26980/601.1667Hz). This sampling rate corresponds to the Nyquist frequency of 22.44Hz. Because the response is mainly observed in the frequency range of 0–5Hz, the signal is re-sampled at every fourth point resulting in the Nyquist frequency of 5.61Hz.

2 Next, an individual signal is divided into two parts. The first halves of Signal 1 and Signal 2 are employed to generate the reference database. Because each signal consists of 6745 (=26980/4) points after decimation, the first half of the signal is now composed of 3372 points. This 3372 point signal is further divided into smaller overlapping segments. The length of a single segment is set to be 1148. (The selection of this segment length is described later.) Therefore, 2225 (=3372−1148+1) overlapping segments are generated from the first half of Signal 1 using a moving time window with 1148 time points. In a similar manner, 2225 segments are obtained from the first half of Signal 2. Therefore, the reference database consists of a total of 4450 signal blocks.

3 We divide Signal 3 into two parts in the same fashion as in Step 2 and assume either the first or second half of Signal 3 as a new data set. In this example, the whole procedure is demonstrated using the second half of Signal 3. The second half of Signal 3 is further divided into three segments. Note that each segment has the same length of 1148 time points as all the reference signal blocks.

4 For each segment of the new data, the reference signals are looked up and the signal segment that is "closest" to the newly obtained one is found. This procedure can be interpreted as a normalization procedure that finds a reference signal segment recorded under a similar "operational" or "environmental" condition as the newly measured one. The "closeness" between two blocks is measured in the following manner.

4.1 For each segment $x(t)$ from the reference database, construct an AR model with *p* auto-regressive terms. In this example, an AR(30) is constructed and an AR(*p*) model can be written as:

$$x(t) = \sum_{j=1}^{p} \phi_{xj}\, x(t-j) + e_x(t) \quad (1)$$

This step is repeated for all 4450 segments in the reference database.

4.2 Employing a new segment $y(t)$ obtained from the second half of Signal 3, repeat Step 4.1 (Again, segment $y(t)$ has the same length as segment $x(t)$):

$$y(t) = \sum_{j=1}^{p} \phi_{yj}\, y(t-j) + e_y(t) \quad (2)$$

Then, the signal segment $x(t)$ closest to the new signal block $y(t)$ is defined as the one that minimizes the difference of AR coefficients:

$$\text{Difference} = \sum_{j=1}^{p} (\phi_{xj} - \phi_{yj})^2 \quad (3)$$

5 It was assumed that the strain measurements are significantly affected by varying see states. Therefore, it is necessary to separate the changes in the system response caused by the varying structural conditions from changes caused by varying see state. It is assumed that the error between the measurement and the prediction obtained by the AR model ($e_x(t)$ in Equation (1)) is mainly caused by the unknown external input. Based on this assumption, an ARX model (Auto-Regressive model with eXogenous inputs) is employed to reconstruct the input/output relationship between $e_x(t)$ and $x(t)$. (An ARX model is basically identical to an ARMA (Auto-Regressive and Moving-Average) model expect that the input to the ARX model is a known external input rather than white noise.) That is, considering the error term $e_x(t)$ an exogenous input to the system, an ARX(a,b) model is fit to the data to capture the input/output relationship between $e_x(t)$ and $x(t)$. The ARX model is defined as:

$$x(t) = \sum_{i=1}^{a} \alpha_i\, x(t-i) + \sum_{j=0}^{b} \beta_j\, e_x(t-j) + \varepsilon_x(t) \quad (4)$$

where $\varepsilon_x(t)$ is the residual error after fitting the ARX(a,b) model to the $e_x(t)$ and $x(t)$ pair. The feature for the classification of damage status will later be related to this quantity, $\varepsilon_x(t)$. ARX(5,5) is used in this example. Here, the a and b values of the ARX model are set rather arbitrarily. However, similar results are obtained for different a and b values as long as the sum of a and b is kept smaller than p ($a + b \le p$).

6 Next, an investigation is made to determine how well the ARX(a,b) model estimated in Equation (4) reproduces the input/output relationship of $e_y(t)$ and $y(t)$:

$$\varepsilon_y(t) = y(t) - \sum_{i=1}^{a} \alpha_i\, y(t-i) - \sum_{j=0}^{b} \beta_j\, e_y(t-j) \quad (5)$$

where $e_y(t)$ is considered to be an approximation of the system input estimated from Equation (2). Again, note that the α_i and β_j coefficients are associated with $x(t)$ and obtained from Equation (4). Therefore, if the ARX model obtained from the reference signal block $x(t)$ was not a good representative of the newly obtained signal segment $y(t)$ and $e_y(t)$ pair, there would be a significant change in the probability distribution of the residual error, $\varepsilon_y(t)$.

7 Finally the ratio of $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ is defined as the damage-sensitive feature in this particular example. Here, $\sigma(\varepsilon_y)$ and $\sigma(\varepsilon_x)$ are the estimated standard deviations of $\varepsilon_y(t)$ and $\varepsilon_x(t)$, respectively. If the ratio of $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ becomes larger than some threshold value h (>1);

$$\frac{\sigma(\varepsilon_y)}{\sigma(\varepsilon_x)} > h \quad (6)$$

the system is considered to have undergone some structural system changes. However, in order to establish the threshold value, test data need to be acquired under different operational conditions, and the probability distribution of $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ first needs to be estimated. Because the data sets provided are limited, the construction of the threshold value based on a rigorous statistical analysis is not achieved in this study.

4.3 Results

The first example is conducted using the first half segments of Signals 1 and 2 as the reference database. Here, the first half of Signal 3 and the second half segments of Signals 1, 2 and 3 are employed as four testing segments with 3372 time points. Figure 3 shows the measured time series of the four testing segments and the corresponding prediction estimated using the ARX (5,5) models as prescribed in Section 4.2. In Figure 3, the responses in the range of 100–120 seconds are enlarged for better comparison. If the system has experienced a change in structural condition, the standard deviation of new data, $\sigma(\varepsilon_y)$ defined in Equation (6), is expected to increase compared to the standard deviation of the reference signal, $\sigma(\varepsilon_x)$. For example, as shown in the first row of Table 2, $\sigma(\varepsilon_y)$ of the second half of Signal 1 increased about 57% from that of the selected reference signal blocks. (As mentioned earlier, each testing time series consist of 3372 points and they are further divided into 3 segments with 1148 points. $\sigma(\varepsilon_y)$ and $\sigma(\varepsilon_x)$ are computed based on all the residuals obtained from these three segments.)

A smaller increase in standard deviation, 26%, is observed for the second half of Signal 2. However, as expected, the standard deviations of the first or second halves of Signal 3 significantly differ from those of the selected reference signals. The standard deviations of the residual errors increased by 126% and 128%, for the first and second halves of Signal 3, respectively. A similar analysis, using the second half segments of Signals 1 and 2 as the reference signals, is presented in the second row of Table 2. In this second example, the first half segments of Signals 1, 2, and 3, and the second half of Signal 3 are employed as testing data sets. Again, a larger value in the $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ ratio is found for the residuals from Signal 3 than those from either Signal 1 or Signal 2.

Third, similar tests are repeated 20 times by randomly drawing testing signal blocks from Signals 1, 2 and 3. For the first 10 random tests, the first halves of Signals 1 and 2 are used as the reference signals, and 10 testing signal blocks are sampled from each of the first half of Signal 3 and the second half segments of Signals 1, 2 and 3. That is, 4 signal blocks are sampled from Signals 1, 2, and 3 for an individual test. Each signal block consists with 1148 time points as done in the previous examples. Testing blocks for the next 10 tests are collected from the first halves of Signal 1, 2 and 3, and the second half of Signal 3 because the second halves of Signals 1 and 2 are used as the reference signals. To summarize, 20 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 summarized in Table 3. On average, the 20 testing blocks sampled from Signal 1 have $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ value of 1.5187. The average value for the 20 signals from Signal 2 is 1.4321. On the other hand, the 40 blocks sampled from Signal 3 have much larger increases in standard deviation. The average value is about 2.2808 (= (2.1902+2.3713)/2).

In Figure 4, separation of Signal 3 from Signals 1 and 2 is attempted by setting the threshold value in Equation (6) to be 1.85. This threshold value (h=1.85) results in only 4 misclassifications out of 80 tested cases. That is, 95% of the tested blocks are correctly assigned to their structural conditions. 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. However, it was shown 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. The additional studies with randomly selected testing signals showed no false-positive indication of damage, and discriminate Signal 3 from Signals 1 and 2 with a 95% of success rate. It should be noted that the separation of the two structural conditions is conducted in a supervised learning mode because the construction of the threshold value requires the acquisition of data from both of structural conditions.

Table 2: Extracted feature: standard deviation ratio of the residual errors

Feature	Signal 1		Signal 2		Signal 3	
	1st	2nd	1st	2nd	1st	2nd
$\sigma(\varepsilon_y)$	Ref.†	1.5667	Ref.†	1.2609	2.2625	2.2811
$\sigma(\varepsilon_x)$	1.5045	Ref.†	1.3995	Ref.†	2.6209	2.5827

† Signal segments with the "reference" notation are used as part of the referen database.

Table 3: The average ratio of standard deviations for randomly selected 20 signal blocks

Test #	$\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$			
	Signal 1	Signal 2	1st half of Signal 3	2nd half of Signal 3
Mean	1.5187	1.4321	2.1902	2.3713

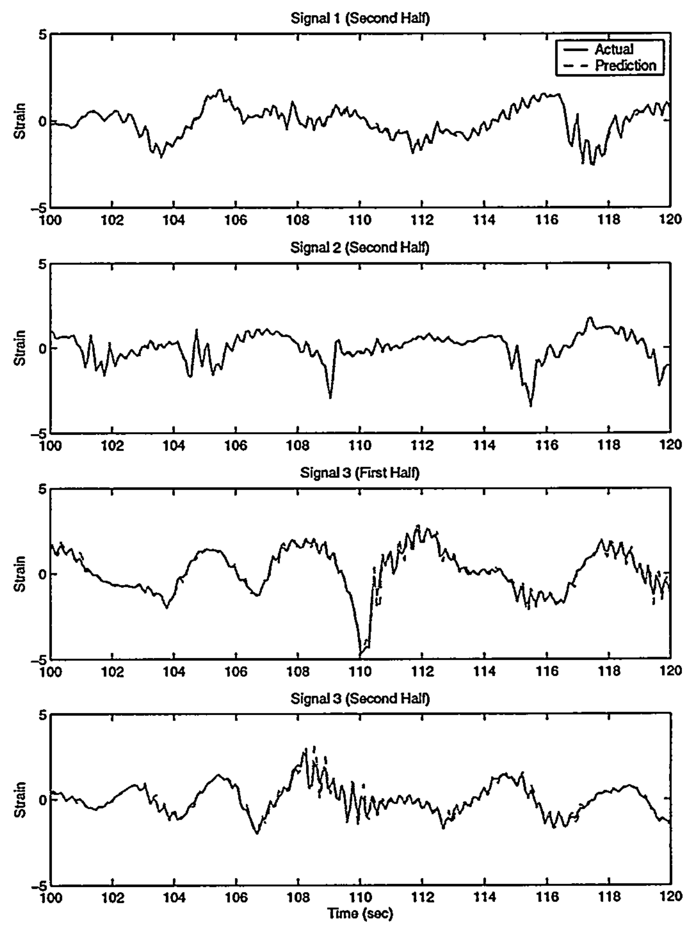

Figure 3: Comparison of the measured vs. predicted signals (zoomed)

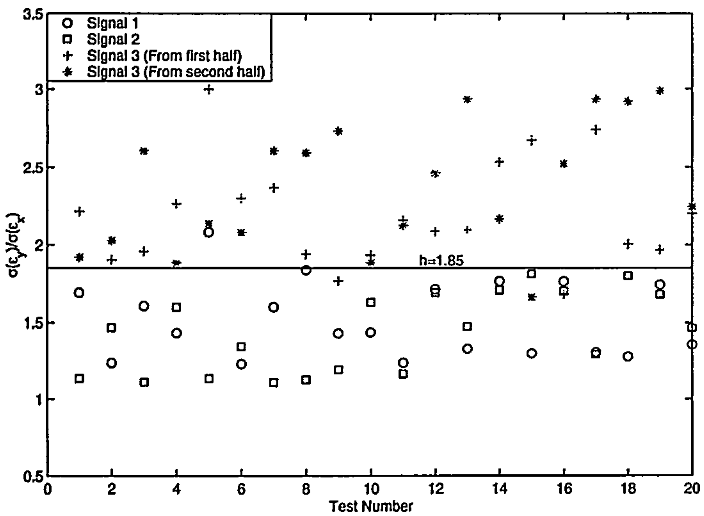

Figure 4: Separation of Signal 3 from Signals 1 and 2 using the ARX residual errors

5. 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 nomalization, feature extraction, and statistical model development. Three strain measurements obtained from a surface-effect fast patrol boat was studied in this paper. 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.

Following the proposed local ARX technique, this study successfully identifies features from the strain time histories that distinguish Signal 3 from Signals 1 and 2. The feature employed in this study, the standard deviation ratio, showed a clear distinction between Signal 3 and Signals 1 and 2. Also Signals 1 and 2 appeared to be similar when compared through this feature. To validate the proposed approach, 80 signal segments are randomly sampled for damage classification. Out of 80 tested cases, there were only 4 misclassifications. That is, 95% of the tested signal blocks are correctly assigned to their actual structural conditions. Finally, out of 40 segments obtained from Signals 1 and 2, there were only one false-positive indications of damage and the rest of 39 cases are correctly assigned to "Structural Condition 1."

It should be noted that *a priori* knowledge that Signal 1 and 2 came from the same structural state was necessary to develop the discrimination procedure present. That is, the discrimination procedure was developed in a supervised learning mode. It should be pointed out that the procedure developed has only been verified on a limited amount of data. Ideally, it would be necessary to examine many time records corresponding to a wide range of operational and environmental cases as well as different damage scenarios before one could state with confidence that the proposed method is robust enough to be used in practice.

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