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Developing an integrated software solution for active-sensing SHM

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Abstract. A novel approach for integrating active sensing data interrogation algorithms for structural health monitoring (SHM) applications is presented. These algorithms cover Lamb wave propagation, impedance methods, and sensor diagnostics. Contrary to most active-sensing SHM techniques, which utilize only a single signal processing method for damage identification, a suite of signal processing algorithms are employed and grouped into one package to improve the damage detection capability. A MATLAB-based user interface, referred to as HOPS, was created, which allows the analyst to configure the data acquisition system and display the results from each damage identification algorithm for side-by-side comparison. By grouping a suite of algorithms into one package, this study contributes to and enhances the visibility and interpretation of the active-sensing methods related to damage identification. This paper will discuss the detailed descriptions of the damage identification techniques employed in this software and outline future issues to realize the full potential of this software.

Keywords: structural health monitoring; active-sensing; damage detection; damage diagnostics.

1. Introduction

Structural health monitoring (SHM) is the process of measuring the dynamic response of a system and determining from these data the current state of the system's "health" in near real time. This process is typically carried out by comparing the dynamic response of an undamaged, baseline structure to that of the current, potentially damaged structure. The advantages of SHM include the possible detection of damage at its onset, before it has had a chance to propagate, thus reducing the potential for catastrophic failure (Farrar, *et al.* 2001, Worden and Dulieu-Barton 2004). These processes must be implemented through hardware or software and, in general, some combination of these two approaches will be used. To date, however, there have been a limited number of technology development efforts that have approached the SHM problem in an integrated manner. Instead, most efforts have focused exclusively either on the sensing technology or the data interrogation algorithms.

As the SHM field grows and matures, the SHM process must make the transition from research practice to real-world field applications. The authors have attempted to develop an integrated software

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solution for piezoelectric active-sensing SHM techniques in order to facilitate this transition. This software is referred to as HOPS (Health of Plate Structures), which allows the analyst to configure a data acquisition system and display the results in a side-by-side comparison. The grouping of a suite of algorithms into a single package enhances the visibility and interpretation of the active-sensing methods related to damage identification in a structure. The algorithms used for signal processing were written as MATLAB functions and integrated using a MATLAB graphical user interface (GUI). HOPS is designed to communicate directly with SHM data acquisition systems. For the case where the hardware is not supported by HOPS, data can be imported using the included data import utility.

Three main categories of structural health monitoring processes are utilized in HOPS. The first process is for the diagnostics and validation of the active-sensors. Sensor diagnostics is a critical step in the SHM process because it is important to identify if a change in readings is caused by a damaged sensor, or damage within the structure itself. The second SHM process involves the comparison of electro-mechanical impedance measurements. The third process incorporates a set of damage identification techniques which make use of measurements from guided waves. More detailed descriptions of the damage identification techniques can be found in the next sections.

2. HOPS signal processing algorithms

Three main categories of structural health monitoring techniques are utilized in HOPS, sensor diagnostics, impedance-based analysis, and guided wave base techniques. The algorithms are written as MatLab functions and integrated by use of a MatLab GUI. The system is designed to communicate automatically with the data acquisition system, integrating the software and hardware components of the SHM system. Descriptions of the algorithms follow.

2.1. Sensor diagnostics

A critical aspect of the piezoelectric active sensing technologies is that usually large numbers of distributed sensors and actuators are needed to perform the required SHM process. In addition, the structures in question are usually subjected to various external loading and environmental conditions that may adversely affect the functionality of SHM sensors and actuators. The piezoelectric sensor/actuator self-diagnostic procedure, where the sensors/actuators are confirmed to be operational, is therefore a critical component to successfully complete the SHM process.

The principle of sensor self-diagnostics is to track the changes in the capacitive value of a piezoelectric (PZT) material, which shows up distinctly in the imaginary portion of the electrical admittance. This portion of the electrical admittance is a function of the geometry constants and the mechanical and electrical properties of a PZT transducer. Thus, breaking of the sensor and the subsequent degradation of the sensor parameters can be identified by monitoring the imaginary portion of the electrical admittance. It has been also found that the changes in bonding condition of a PZT transducer significantly affect the capacitive value of a PZT material, which allows one to obtain critical information on the functionality of the transducers. A more detailed description on the sensor diagnostic process can be found in the reference (Park, *et al*. 2006a, 2006b).

HOPS performs the sensor diagnostics in two different ways. The first is to compare readings from each sensor with baseline readings from that sensor. This process requires the storage of the initial baseline readings. The second technique is to compare readings from every sensor to each other rather than a baseline. This algorithm takes advantage of the observation that the removal of an unhealthy sensor will cause a greater decrease in the standard deviation of the group of sensors than with the removal of a healthy sensor (Overly, *et al*. 2008a). This second technique eliminates the need for a pre-stored baseline, only requiring a single current set of readings from each sensor.

2.2. Impedance-based SHM method

Impedance based structural health monitoring methods use high-frequency structural excitations, typically higher than 30 kHz, through surface bonded piezoelectric patches to monitor changes in structural mechanical impedance. The electrical impedance is a function of the mechanical impedances of the PZT actuator and the host structure. Assuming that the mechanical impedance of the PZT patch does not change over time, any changes in the electrical impedance measurement can be considered an indication of a change in the mechanical impedance of the host structure. A change in the mechanical impedance of the host structure is due to damage. The change in impedance due to damage is exhibited in the real portion of the impedance signature (Park, *et al*. 2003, Giurgiuitiu, *et al*. 2004, Bhalla and Soh 2003, Park, *et al*. 2007).

Two simple statistical algorithms are adopted in HOPS for a quantitative assessment of damage using impedance methods. The first is to find the cross-correlation coefficient between the baseline and test signals. The cross-correlation coefficient between the two data sets determines the linear relationship between the two signals. The cross-correlation coefficient is subtracted from one yielding a damage index between 0 and 1, where larger values indicate a greater extent of damage. The second method is based on a frequency-by-frequency comparison and is referred to as the root-mean-square-deviation (RMSD) and is defined as:

$$M = \sum_{i=1}^{n} \sqrt{\frac{[\mathrm{Re}(Z_{i,1}) - \mathrm{Re}(Z_{i,2})]^2}{[\mathrm{Re}(Z_{i,1})]^2}} \tag{1}$$

where M is the damage metric, $Z_{i,1}$ is the impedance of the baseline measurement, and $Z_{i,2}$ is the test measurement at frequency interval i. The aforementioned cross-correlation coefficient and RMSD have been traditionally and mainly used in electro-mechanical impedance analysis for SHM (Park, *et al*. 2003).

This portion of HOPS is also equipped with a hardware control module. This control module is made to be available for both the impedance measurement and sensor diagnostic processes, which would allow for data to be acquired for sensor validation and SHM purposes. This module allows for the direct control of an Agilent 4294A impedance analyzer and wireless impedance device that was developed by the authors (Overly, *et al.* 2008b). The acquisition module reduces the time required to measure multiple PZT transducers and eliminates the formatting issue associated with data coming from multiple sources.

2.3. Guided waves

Since the 1960s, the ultrasonic research community has studied Lamb waves for the nondestructive evaluation of plate-like structures (Bourasseau, *et al*. 2000). The advances in sensor and hardware technologies for efficient generation and detection of Lamb waves and the need to detect sub-surface damage in laminate composite structures has led to a significant increase in the use of Lamb waves for detecting defects in structures (Alleyne and Cawley 1992, Rose 1999, Kessler, *et al*. 2002, Lee and Staszewski 2003, Giurgiuitiu, *et al*. 2004, Ihn and Chang 2004, Croxford, *et al*. 2007).

Lamb waves are mechanical waves corresponding to vibration modes of plates with a thickness on the same order of magnitude as their wavelength. Lamb waves couple longitudinal and shear waves of plane strain within a plate that propagate in a variety of modes that are either symmetric or antisymmetric. To dates, several methods have been proposed to enhance the interpretation of the measured Lamb wave signals to detect and locate structural damage. They are based on changes in wave attenuations using wavelets (Kessler, *et al*. 2002, Sohn, *et al*. 2004), time-frequency analysis (Ihn and Chang 2004), wave reflections (Giurgiutiu, *et al*. 2004, Diamanti, *et al*. 2005), and time of flight information (Lemistre and Balageas 2001).

As stated, guided wave-based SHM methods can make use of many different features in an attempt to detect damage. With this in mind, HOPS currently employs three different signal processing methods and includes framework to add additional methods. A hardware control is also available for direct data acquisition and on-line damage detection.

2.3.1. Wave attenuation

As Lamb waves propagate through a structure, the mechanical energy is usually dissipated due to internal damping in a structure, causing a decrease in the magnitude of the wave. The amount of attenuation between two points on a structure changes when damage is located in the path between them. By comparing the amplitude of the packets in a baseline measurement to those in a test measurement, conclusions can be made about the existence of damage between the actuator and sensor. The attenuation feature can be used to identify the existence of damage, however a single sensor pair can make it difficult to determine the exact location of the damage. Therefore, an array of PZT transducers with multiple paths is usually employed to determine damage location.

To achieve an attenuation comparison between a baseline measurement and a test measurement, both signals are transformed using a wavelet transformation in HOPS. Then, a damage index (DI) can be calculated based on a ratio of the kinetic energy of the test signal to that of the baseline, as in Eq. (2).

$$DI = \left| \frac{\int_{u0}^{u1} Wf_t(u, s_0)du - \int_{u0}^{u1} Wf_b(u, s_0)du}{\int_{u0}^{u1} Wf_b(u, s_0)du} \right| \tag{2}$$

In Eq. (2), the t represents the test signal and b represents the baseline signal, u_0 and u_1 represent the starting and ending time points for the signal. The DI ranges from 0, no damage, to a maximum value of 1 as the attenuation increases. A more detailed description of the technique can be found in Sohn, *et al*. (2004).

Once the damaged paths have been determined, they are plotted on a predefined grid. The number of damaged paths intersecting at each grid point is divided by the number of undamaged paths intersecting at that point. The result is then normalized over the entire grid. The normalized values are plotted on a grid in the HOPS user interface to indicate the most likely locations of damage (Swartz, *et al*. 2006).

2.3.2. Power spectral density

A second method of feature extraction for the Lamb wave data involves the cross-correlation of the power spectral density functions between the baseline and test signals. When a wave passes through damage, such as corrosion or a crack, the wave is scattered, referred to as mode conversion, causing a change in the frequency content of the signal. By looking at the degree of change of the frequency content, one can determine that a path contains structural damage. After measuring the propagated wave, the power spectral density (PSD) is calculated for a band about the excitation frequency for the baseline and test signals. As in the work by Swartz, *et al.* (2006), the DI is based on the cross-correlation coefficients of the two PSDs, which identify the shape changes in PSD curves, and detect the frequency content distortion. For consistency with the other feature extraction methods, the cross-correlation coefficient is subtracted from one, so that the signals with the highest correlation (the lowest amount of damage) have a damage index very close to zero, while signals with low correlation (high amounts of damage) have a higher damage index.

2.3.3. Triangulation of reflected waves

When Lamb waves travel through damage, some of the waves can be reflected due to the presence of damage, creating new wave arrivals in the received signal. The third method of feature extraction for Lamb waves uses the reflection features to locate the damage. For this process in HOPS, a wavelet transform is first performed to denoise the measured signals. Then, the arrival time for the first wave is calculated for each path to determine the wavespeed. The baseline signal is then subtracted from the test signal, leaving only the reflections. A Hilbert transform is then performed on the reflections signal to calculate the corresponding analytic signal, the magnitude of which is the signal's envelope. Peaks in the envelope pinpoint the arrival times of the reflections. Using the wavespeed, the distances traveled by the reflections are calculated. With the travel distance of each reflection, an ellipse is drawn around the sensor pair indicating where the reflection could have originated. Crossing of ellipses from multiple sensor pairs reveals the damage location.

3. HOPS software

HOPS user graphical interface is created to merge the various SHM signal processing method described in the previous section, as shown in Fig. 1. There are three main panels in HOPS: *Setup*, *Current Data*, and *SHM*.

The *Setup* panel contains links to the geometry module that let the user configures the structural parameters and the sensor/actuator configuration, and the data import module that can transport data for being processed in HOPS. *Current Data* is a panel that allows for the manipulation of the currently loaded data. This manipulation of the data includes saving it to a new file, clearing it for other modules or loading a previously recorded data set.

The final panel, *SHM*, includes three links to modules that do the brunt of the SHM analysis. The three main capabilities include the analysis of Lamb wave propagations, the analysis of impedance based measurements and the diagnosis of sensor condition. Hardware control functions are embedded in each module to collect live data as needed. The program is also designed in such a way that the measured data and the hardware parameters can be dynamically saved and loaded for future analyses. Data and variables are passed between modules through the main function. By integrating hardware and several signal processing algorithms into one package, HOPS can be an efficient and integrated SHM tool for various applications, allowing the uses to select the most suitable algorithm for different forms of damage.

Fig. 1 HOPS main function GUI

4. Experimental setup and procedure

Experiments were performed to investigate the performance of HOPS. The test structure was an aluminum plate instrumented with an array of piezoelectric transducers. The sensor diagnostics process was first carried out in order to assess the sensor installation condition. Damage to the structure was introduced in the form of corrosion, which is the most typical type of damage in aluminum plates. Impedance and guided wave measurements were then taken before and after damage to assess the condition of the plate. All the signal processing was performed using HOPS and only selected results are presented due to the space constraints of the paper.

An aluminum plate used in this study had dimensions of 1219 mm square. The plate was instrumented with nine PZT transducers, which were spaced at 304.8 mm to create a 3 by 3 array configuration. One side of the plate had 6.25 mm diameter circular PZT transducers. The PZT transducers

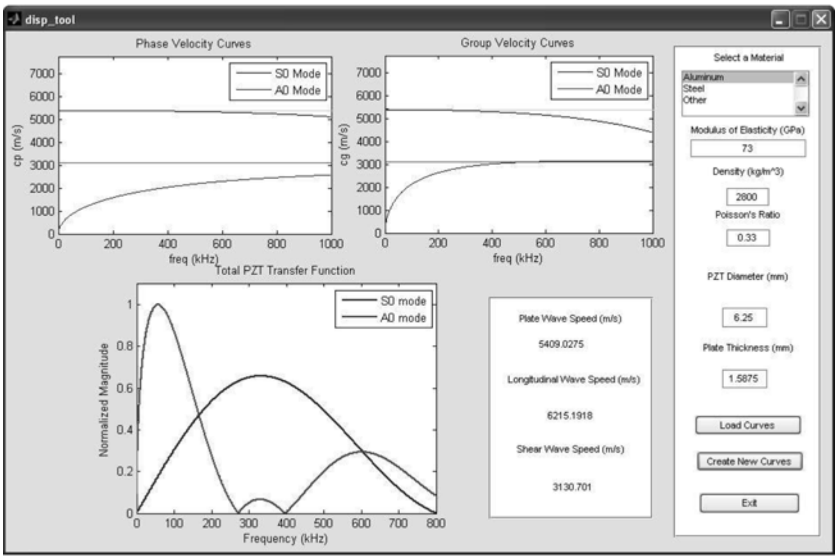

Fig. 2 Dispersion curve and transfer function tool

were bonded to the plate using a quick-setting adhesive. The impedance and sensor diagnostic data were collected with an Agilent impedance analyzer. The Lamb wave data are acquired using a commercial system capable of sampling up to 25 MHz. Damage was introduced in the form of corrosion. A mixture of water and table salt, an aluminum cathode and a power supply are used to introduce corrosion. Measurements are taken after each stage of the damaged conditions.

To perform the sensor diagnostics test, a frequency range of 1 - 20 kHz was used. For the impedance test, the frequency range of interest was 185 kHz to 190 kHz. This range contains several peaks and does not contain the natural frequency of the PZT transducer, so it is a useful range for obtaining information about the health of the plate structure. Two different frequencies were used for the guided wave portion of the study, 80 and 250 kHz. The driving frequencies for the various modes are dependent on the size of the PZT used and the structure monitored. Included in HOPS is a tool that creates the group and phase velocity of the plate and transfer functions of PZT transducers that helps to select the desired driving frequency. This tool is embedded in the wave propagation module. Fig. 2 shows the curves from the tool for a 1.59 mm plate and 6.25 mm diameter transducers.

5. Demonstration of HOPS

The experimental results illustrate the performance of HOPS. Each module and each signal processing techniques are utilized in order to provide the effectiveness of the software.

5.1. Geometry and data import

In HOPS, the Geometry module allows the user to define the size and the shape of the structure,

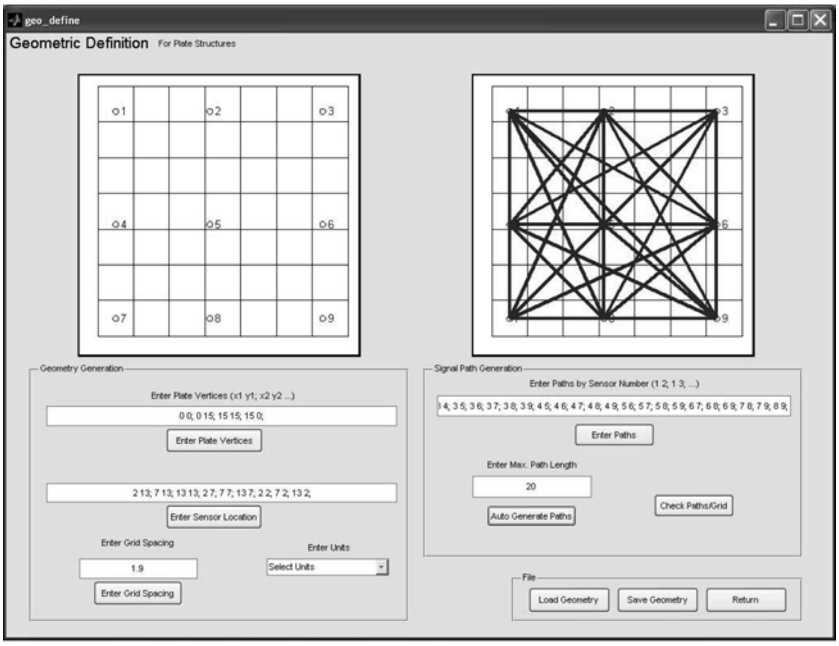

Fig. 3 Geometry module GUI

sensor locations, the size of a grid to be used for locating damage, and the sensor paths that can be used for the Wave Propagations. Data collected with programs other than HOPS can be imported using the Import Data module. The geometry and the automatically generated sensor paths defined for the test structure are shown in Fig. 3.

5.2. Sensor diagnostics

Sensor diagnostics are then performed to confirm if all of the sensors are functioning properly and are all bonded to a similar level. As is shown in Fig. 4, there are several key features to this interface. The first is the ability to select any of the past measurements in the file for analysis. The *Measurement* panel is where the measurement is selected and allows for comparison over time. The second important feature is the ability to select the number of data points to be included. This selection is important to avoid possible structural resonances that could invalidate the algorithm. This parameter is set in the *Analysis Information* panel. Beyond these two user selectable parameters, the algorithm works as developed in Overly, *et al.* (2008a).

The algorithm takes advantage of the characteristic that the removal of an unhealthy patch will cause a greater decrease in the standard deviation of the group of sensors than with the removal of a health sensor. The output of the proposed algorithm is a hybrid plot with the upper plot showing all of the admittance measurements with color coding corresponding to the lower plot. The lower plot shows the effect of the reducing the sample number with the x-axis showing which sensors are recommended for replacement. The lower plot also has a line delineating the healthy patches from the unhealthy ones. When the algorithm was run on the plate, one sensor (sensors 1) on the Aluminum plate was recommended for replacement because of the poor bonding.

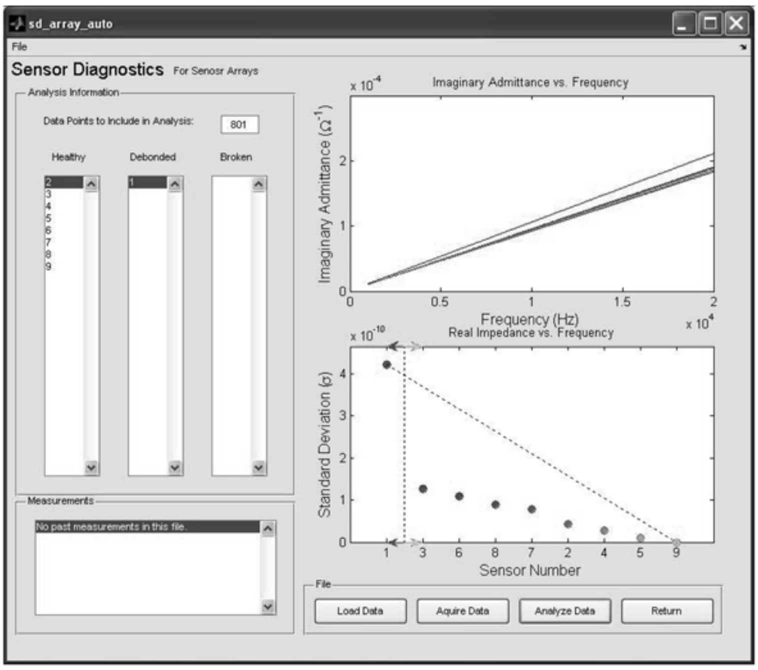

Fig. 4 The sensor diagnostic module automatically determines which sensors are broken or debonded

The effects of the active-sensor defects on high frequency structural health monitoring techniques are found to be significant, modifying the magnitude and the shape of the propagated Lamb waves, and influencing the measured magnitude and resonances of the electro-mechanical impedance spectrum (Park, *et al.* 2006b). These changes could be registered as structural damage unless an efficient sensor-diagnostic process is implemented in the practice. As shown, with this sensor diagnostic module, HOPS is able to differentiate signal changes caused by damage from those due to sensor failures.

5.3. Impedance analysis

The impedance analysis was performed to detect structural damage. Corrosion was introduced between sensor 1 and 2 with 30 mm diameter and 0.86 mm deep. Only five sensors were used to measure the impedance, sensors 1, 3, 5, 7 and 9. This procedure is taken as the impedance method is not able to pin-point the location of damage, rather this method only gives the estimated area of structural damage. PZT sensors 1, 3, 5 were able to detect the presence of damage by showing damage index values in the range of 135-158 (RMSD) and 0.58-0.72 (Correlation), while PZT sensors 7 and 9 showed in the range of 20-30 (RMSD) and 0.08-0.1 (Correlation). As shown in Fig. 5, this module displays cross correlation and RMSD damage index, as well as the measurements taken for visual comparison. HOPS also changes the color of the graphical representation of the sensors to red (as shown in Fig. 5) suggesting that the area close to these sensors might be damaged. The impedance analysis module has also the ability to select any of the past measurement in the file for the SHM analysis, and the user can set the threshold limit for sensor damage identification dynamically by looking at the statistics values in conjugation with the graph provided. In such a way, misclassification (false-positive or false-negative) can be reduced.

HOPS is designed to store the measurement history into a database, so that one can track the variation

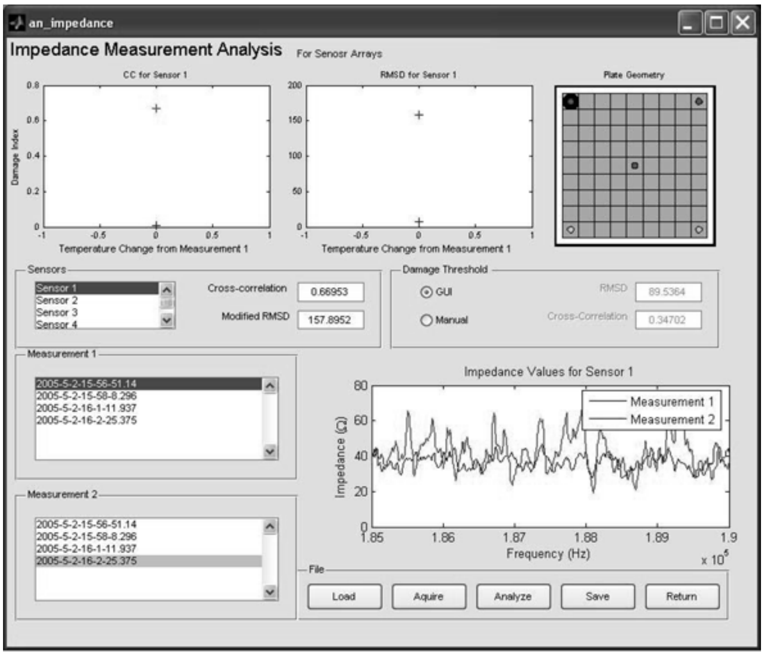

Fig. 5 Impedance analysis for corrosion detection

of signatures usually caused by environmental or operational condition changes. By doing so, the variation of SHM algorithms can be identified and the threshold level for damage identification can be established. Both damage indices for sensors 1, 3 and 5 were well above the variation that was observed from temperature variations, while the variation in the damage indices for sensors 4 and 5 were within the normal variation. By referring the history of signature variation in the past, the users can dynamically set the threshold limit to increases the ability to detect the presence of damage.

5.4. Guided wave analysis

In HOPS, the Wave Propagation Module displays the results of the various analysis techniques for a side-by-side comparison. Fig. 6 shows the Wave Propagation Module with data for the corrosion damage from the piezoelectric transducers. The left side of the module will define the data acquisition parameters, such as a sampling frequency, excitation frequency, number of average, and number of data point taken. The right side of the module displays the result of damage detection using different signal processing algorithms.

The upper-left figures show the results using the wave attenuation feature. The attenuation of the fundamental symmetric mode is found to be sensitive to corrosion damage. Sensor paths crossing the corrosion damage indices as large as 0.86. The damage location algorithm successfully identifies the damaged paths in all damage cases for both plates. A summarization of the mean damage indices for damaged and undamaged paths for all cases is shown in the Fig. 6. These paths are then used to locate the damage on a user-defined grid. The grid size used for this study is 30 mm by 30 mm. The state of damage for a given grid location is indicated by the intensity of the color displayed, which is a function of the probability that that grid is damaged. The probability is based on the number of damaged paths intersecting the grid location versus the number of undamaged grid lines.

As in the Impedance Module, databases of damage indices history are created for each measurement. HOPS also allows to display the response of each path by pressing the “view set button. Fig. 7 displays

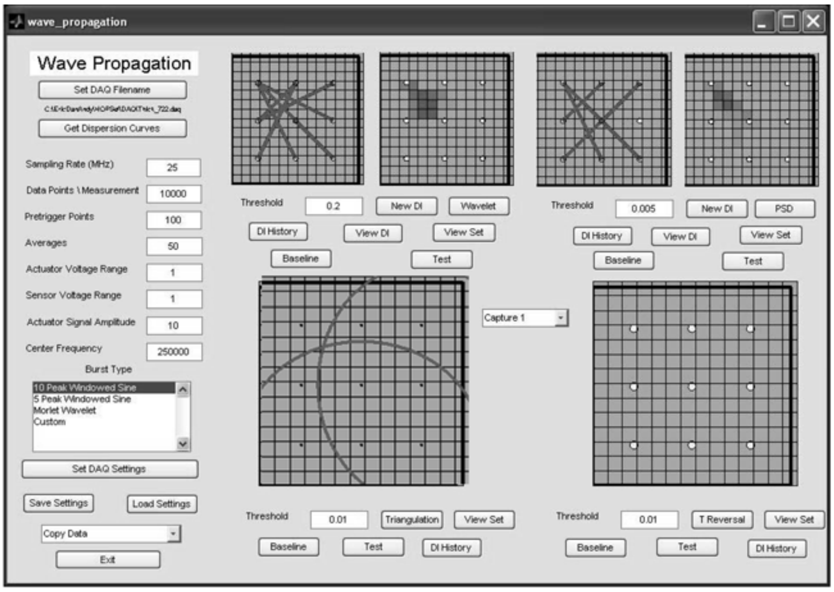

Fig. 6 A snap shot of HOPS wave propagation module

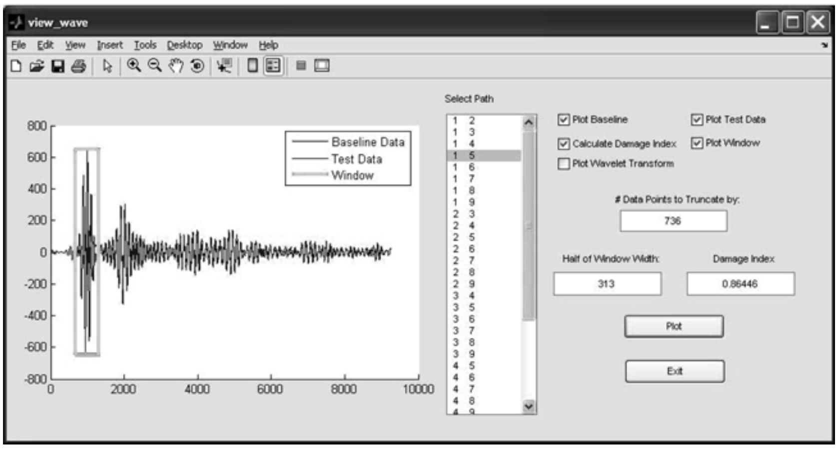

Fig. 7 A snap shot of HOPS that displays the response of each path

the baseline and a test measurement for visual comparison. Any response from each path can be automatically displayed by clicking the corresponding path.

Similar results were obtained using power spectral density function as well as Triangulation of Reflected Waves, as shown in Fig. 6. New signal processing algorithms could be easily implemented into HOPS as they are developed.

6. Discussion

Specific topics that have not been extensively addressed in the SHM literature are i) the development of user friendly and automated software for data analysis; ii) coupling the sensing hardware directly with SHM data interrogation software. This work is trying to address these issues, and the successful studies toward these areas will help to transition the current state of SHM to full-scale industrial adoption. By integrating various data interrogation and signal processing algorithms, a powerful SHM tool has been developed that can be applied to a wide variety of applications. By integrating the software and hardware functions into one package and automating the process, the burden for the analyst is significantly reduced.

Each algorithm produces various levels of efficacy based on the type of damage present. For example, the analyst could perform an impedance test to determine if damage is present in the structure. Then, the analyst could estimate if the damage is in the structure or the sensors themselves using the sensor diagnostic process. If the analyst determines that damage is present, wave propagation could then be used to locate the damage. Including the ability to compile a database of baseline values gives the analyst the ability to determine if changes detected by the SHM algorithms are statistically significant and thus due to damage and not the normal changes caused environmental conditions.

7. Conclusions

This study developed an automated and integrated active-sensing SHM system for various applications. The use of a suite of SHM signal processing algorithms provides the analyst with a richer output than would a single algorithm alone. The effectiveness of each of these signal processing algorithms for SHM is then compared and demonstrated. Although this study focuses on the monitoring of an aluminum panel only, the software developed in this research can be adapted into a variety of structural health monitoring applications.

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