

Autonomous Impact Damage Detection and Isolation Prediction for Aerospace Structures

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Abstract: This paper presents a practical yet innovative impact damage identification and prognosis approach for aerospace structures that uses an optimized suite of reliable COTS sensors coupled with advanced damage detection and modeling algorithms. The presented methodology utilizes a monitoring approach based on acceleration measurements that are analyzed using advanced signal processing and dispersive wave theory models that capture frequency and orientation dependent wave propagation effects. The acceleration measurements and associated processing modules are used to provide immediate detection and isolation estimates, while an energy amplitude feature allows for assessments of damage severity after the impact. By embedding wave theory model results with the adaptive signal processing algorithms, a more accurate understanding of the time-frequency behavior of the dispersive waves produced at impact is gained. Damage localization is performed based on the comparison between the predicted and measured wave group velocities, with a genetic algorithm used to optimize the parameters of a triangulation procedure. This combination of model and feature-based algorithms allows the system to make use of limited, but readily available accelerometer data. This procedure also minimizes the learning and modeling difficulties associated with other techniques that are based solely on models or measurements. A few selected demonstrations are presented that illustrate the impact location prediction capabilities in realistic carbon fiber reinforced polymer (CFRP) composite panels.

TABLE OF CONTENTS

- 1. Introduction
- 2. Feature-Based (Signal Processing) Approach
- 3. Wavelet Basics
- 4. Model-Based (Finite Element & Dispersive Wave Theory) Approach
- 5. Experimental Test Bed and Results
- 6. Conclusions
- References
- Biographies

INTRODUCTION

Applications for structural composites used in the aerospace industry often undergo high-stress loading profiles and operational impacts that can produce various types of damage, including fiber breakage, matrix cracking, delamination and interface de-bonding. The result of such damage can have detrimental effects on the overall strength of a vehicle in terms of its ability to complete its mission or compromise the safety of the crew. The need for practical, reliable and non-intrusive technologies for continuously assessing and monitoring the health state of complex aerospace structures is required in order to improve vehicle availability and reduce the safety risks and total ownership cost through elimination of costly inspection processes.

In addition, current structural fatigue prediction and damage detection methods have not kept pace with the increasing performance requirements and the use of new materials, nor with the need to use aircraft beyond their designed service lives. Next generation structural health monitoring systems (SHM) need to be capable of operating at both the local or global levels, and provide a means to significantly reduce life cycle costs of aerospace structures by providing accurate real-time assessments of structural damage. These considerations highlight the pressing need for innovative signal analysis and damage classification techniques based on practical measurements such as accelerometers embedded in CFRP structures.

A review of the literature [1-6] indicates that there continues to be a need for reliable strategies in structural health monitoring (SHM) that are robust enough to be of practical use on aerospace systems. A few of the drawbacks of current SHM methods include:

- Current structural monitoring implementations are typically accomplished with a limited number of sensors, dispersed over a relatively large area of a structure. These sensing systems can only provide the spatial resolution to detect fairly significant damage and can not locate damage accurately. Recent advances in sensing and on-board processing technologies are making it more feasible and

affordable to collect larger amounts of data for long-term continuous monitoring of in-service structures.

- Current off-line, non-destructive inspection systems require data analysis to be manually performed by experienced engineers, with automation of this data analysis remaining largely unsolved. For continuous, real-time monitoring, it will be critical to reduce unnecessary interfaces by end-users and to automate the data analysis process throughout a distributed health monitoring system architecture.
- Current damage detection techniques have been successfully applied to scaled models or specimens tested in controlled environments, the performance of these techniques in real operational environments needs to be further developed and validated. Varying environmental and operational conditions produce changes in the system's dynamic response that can be easily mistaken for damage. Hence a need still exists for damage detection algorithms that will minimize false positive and negative indications of damage.

The technology components necessary to develop a more reliable impact damage assessment and prediction system should include proven, air-worthy measurement technologies and an associated set of validated, real-time analysis techniques that can provide a comprehensive and updated correlation with the health state of the structure. Hence, establishing *quantitative* links between specific damage types, size and location based on measured changes from highly sensitive signal processing and model-based technologies such as wavelet transforms and dispersive wave theory models is the recommended approach presented herein. Figure 2-1 shows a simple representation of a combined model and feature based procedure for performing damage detection in an aerospace structure. The major elements of this damage prediction process include: data pre-processing and feature extraction, model-based wave arrival time prediction, error pattern classification, data/information fusion and impact predictions. Where the core impact analysis exists in the classification of the differences between the predicted wave group velocities and those measured with the wavelet-processed features.

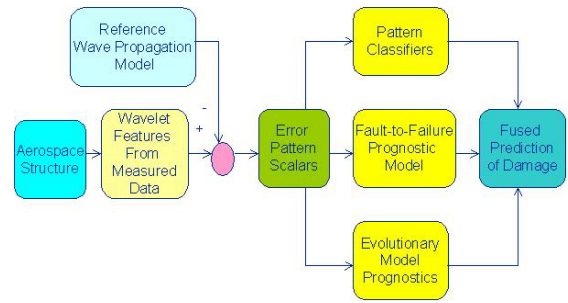


Figure 1 - Model-Based and Signal Processing-Based Analysis for Damage Detection in Aerospace Structures

The project team of Impact Technologies and the University of Dayton Research Institute has developed a series of structural monitoring test beds with the objectives of identifying (a) damage initiation, (b) damage location and (c) severity of damage in composite structures. Figure 2 shows the implementation stages for the damage detection and localization process discussed herein that uses both data-driven and model-based approaches. Specifically, a robust monitoring concept will be presented based on an accelerometer-based sensing system using a series of flat and curved composite panel test beds that was able to provide comprehensive insight into the structure's observed health state. Two different, but collaborative approaches have been developed and assessed in terms of their respective abilities to detect, localize and assess severities of damage events. The first approach described is based on advanced signal processing techniques that utilize wavelet packets, high-order moment statistics, neural networks, and a triangulation procedure. This is also referred to as a "feature-based" approach. The second approach is referred to as "model-based" and utilizes either a Finite Element (FE) model or dispersive wave theory equations of motion to evaluate and extract similar impact damage characteristics. A brief description of each of these approaches and associated results from a subset of tests are presented in the following sections.

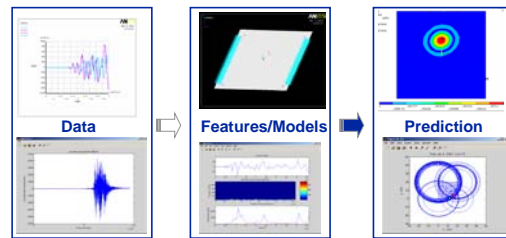


Figure 2 - Damage Identification and Localization Stages

2. FEATURE-BASED (SIGNAL PROCESSING) APPROACH

Complex structures, such as those utilized in aerospace applications, often undergo damage profiles that require non-stationary analysis techniques in order to be capable of detecting them [1, 2]. It is of critical interest to monitor these dynamic signals from inherent structural energy changes and vibration that reflect both the non-stationary components due

to the surrounding excitation and those changes due to the damage itself. Traditional Fourier series analysis models are often inappropriate when used alone, since they require stationary data and do not account for time-dependent considerations. Multi-scale, time-frequency analysis techniques such as wavelets can be applied to this problem to provide a robust framework for efficient analysis of such non-stationary processes [3, 4, 5].

Wavelet transforms have been studied since the fifties by mathematicians, but it has only been in the last ten years that they have made huge advancements in the engineering and signal processing community [6]. The wavelet transform has emerged in many areas of signal processing, such as image processing, data compression, sub-band coding, communications and speech processing. The wavelet transform is favored over the Fourier transform techniques by speech researchers because of the non-periodic segments in a speech signal and the flexibility of the transform. These features make it attractive for structural response analysis as well.

The wavelet transform is particularly effective for representing various aspects of non-stationary signals such as trends, discontinuities, and repeated patterns that have both time and frequency components in them. Wavelet analysis has become one of the most powerful methods in data analysis for damage detection [3, 4, 8]. The advantage of algorithms based on the wavelet transform is that they are able to reveal important temporal and spectral patterns in a signal. These patterns may constitute the signatures of the dynamic events in question and may offer the key to more effective and reliable interpretation of the sensor signals. Wavelets have a built-in “spatial adaptivity” that allows efficient estimation of functions with discontinuities in derivatives, sharp spikes, and discontinuities in the function itself. The power of wavelets is that they capture local scale activity in the data. Transient-detection algorithms based on these adaptive signal-processing concepts can be used to detect, automatically, transient loads so as to provide an accurate statistical characterization of the extreme load history experienced by a structure [11]. A sudden structural stiffness loss may result in a stiffness discontinuity or singularity in acceleration response data, and can be detected by the wavelet approaches due to sensitivity of wavelets to singularities in a vibration signal.

3. WAVELET BASICS

The wavelet transform is an operation that transforms a signal by integrating it with a kernel function. The kernel function or mother wavelet is a function that will be scaled and delayed as it is correlated with the signal of interest during the integration process. The wavelet transform of $f(t)$ with respect to the mother wavelet $g(t)$ is defined as

$$W_g f(s, \tau) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} f(t) g\left(\frac{t-\tau}{s}\right) dt \quad (1)$$

where s is the scale and τ is the delay of the mother wavelet. In the wavelet transform, the kernel function, $g(t)$, is delayed by an amount τ and scaled by an amount s . The scaled mother wavelet is energy normalized by the **Error! Objects cannot be created from editing field codes.** term. A function must be admissible for it to qualify as a mother wavelet. A function, $g(t)$, is admissible if

$$c_g = \int_{-\infty}^{\infty} \frac{G(\omega)}{|\omega|} d\omega < \infty \quad (2)$$

where $G(\omega)$ is the Fourier transform of $g(t)$. The constant c_g is the admissibility constant of the function $g(t)$, and the requirement that it is finite allows for inversion of the wavelet transform. An example of a signal that is not admissible is a sine wave, because the signal has infinite energy. To make a function like this admissible, a Gaussian function can be multiplied by the non-admissible function. A Gaussian weighted tone, which is called a Morlet mother wavelet, has the following form.

$$g(t) = e^{-\alpha t^2} e^{j\omega t} \quad (3)$$

The signal used for the mother wavelet can be user defined and is very flexible. Basically any signal may be used as long as the energy of the signal is finite. This means that a section of the processing signal that represents some significant event may be used. Figure 3 is a block diagram of the implemented wavelet processing procedure presented herein. Utilizing the Morlet mother wavelet as shown above, the signal transient behavior is extracted and retained.

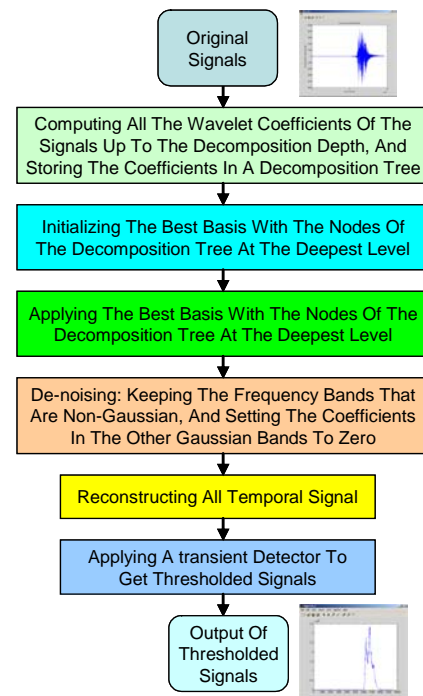


Figure 3 - Transient Detection Using Wavelet Packets and Higher-Order-Statistics

Figure 4 shows the results of the process described in Figure 3, starting with raw data from an accelerometer taken from the test bed discussed in a later section. The data sample acquisition rate was 1.0×10^{-6} samples per second, with the start time of 0 and an end time of 9.549×10^{-3} seconds. Figure 4(b) shows the results using the Morlet wavelet packet decomposition, and Figure 4(c) is the final output of the thresholded signal using an adaptive energy detector.

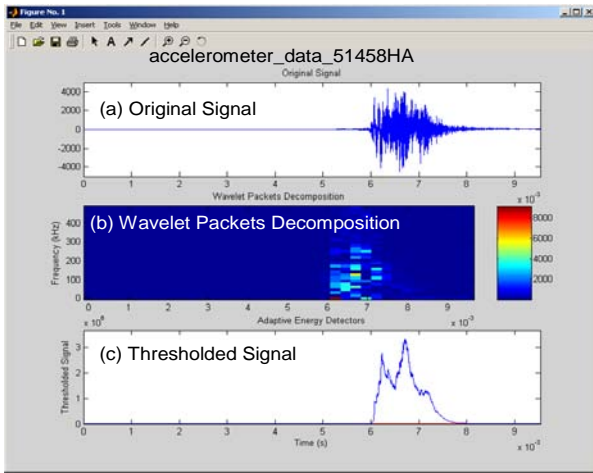


Figure 4 - Original Signal and Wavelet Processing Results for Example Accelerometer

Based on the wavelet transform analysis described above, the next step is to extract specific features that can be used for assessing the impact damage characteristics. The features of interest in determining impact location and severity are related to the time of arrival of the propagating dispersive wave and magnitude of energy received at the accelerometer locations, respectively. Figure 5 shows the entire process associated with the feature-based approach, where the block diagram on the left is specifically used in the training stage and the diagram on the right is implemented during the evaluation stage.

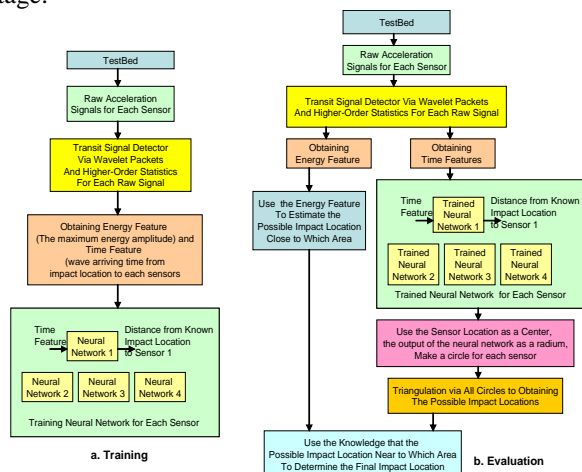


Figure 5 - The Feature-Based Approach for Impact Damage Detection and Localization

Based on the output from the wavelet transform, thresholds are set on the magnitude of the output energy detector in order to calculate the time of arrival of the dispersive wave group velocity. In addition to this time-based feature, an integration of the overall signal magnitude represents an energy feature that is used to locate the approximate area of the impact. Next, a combination of these features is used to perform the final localization with a modified triangulation process. Figure 6 is an example of the features extracted from four accelerometers located at the corners of a 24-inch square plate used in the evaluation process described in a later section.

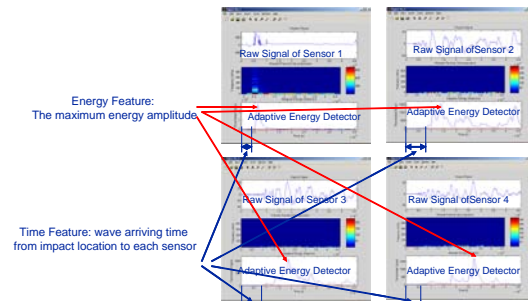


Figure 6 - An Example of Feature Extraction Using Wavelet Packets and Statistics

After performing several impact tests, where the features described above are extracted with known information about the exact locations of the impact, a series of files are logged for training purposes. The energy features are then calculated from the maximum amplitude experienced from the Kurtosis of the output from the wavelet transform. This maximum amplitude feature is then compared with those experienced by all accelerometers to determine the general area of the applied impact. Next, time of arrival features are calculated from each accelerometer based on when the adaptive energy feature exceeds a particular threshold. Based on the number of known cases used in the training file, a simple back-propagation neural network was developed that relates the actual distance of the true impact location to each of the accelerometers. Figure 7 is an illustration of this process as related to the energy and time features.

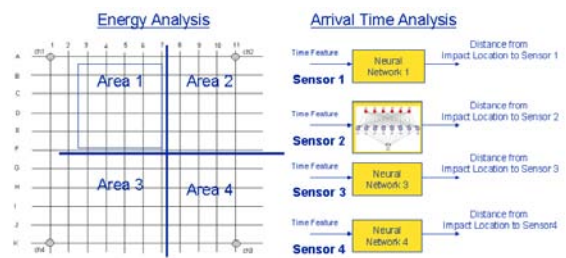


Figure 7 - Energy and Time-Based Features Used in Training Algorithms

A neural network is a data-driven modeling approach that begins its training process with initial weights and constants associated with a selected set of basis functions. Hence, the approach taken in this paper was to train multiple neural networks with initial weights and basis function constants provided by a Monte Carlo simulation procedure. Therefore, the output of each of these trained neural networks with different initial conditions would provide a distance prediction based on the input group velocity arrival time extracted from threshold crossing. An example of the outputs of these networks for a given example is shown in Figure 8. Finally, a prediction on the location of the impact is made based on the intersection of each of the distances predicted from the accelerometers. These predicted distances are shown as concentric circles, with each of the accelerometers representing the centers.

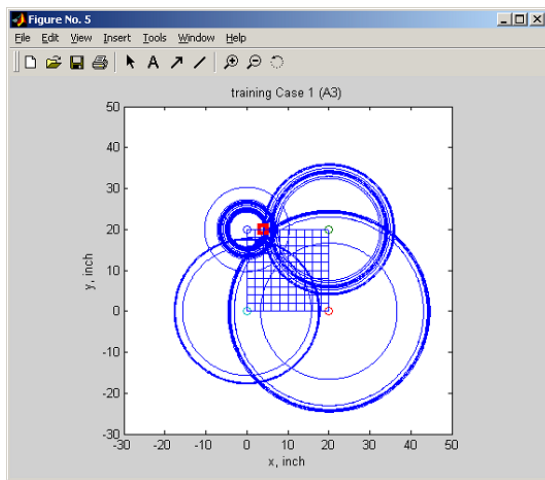


Figure 8 - Example Outputs from Trained Neural Network for Distance Prediction

4. MODEL-BASED (FINITE ELEMENT AND DISPERSIVE WAVE THEORY) APPROACH

Method 1: Finite Element Transient Simulation

The first model-based method described is based on a finite element model transient simulation. In this process, the measured sensor outputs are compared with the predicted responses from the model to determine the impact location. If two responses are not similar in terms of a proximity norm, the algorithm revises the model run to characterize the response from a different impact location. The process is reiterated until the model response and the registered response of the structure match with a required accuracy.

Due to uncertainties associated with boundary conditions, material properties, damping characteristics and shape of the applied impulse, the theoretical response will not have an absolute match with the sensor output. Hence, a good feature for comparison was found to be the time of wave

propagation from impact location to the sensor position, as was used in the feature-based approach already discussed. As a result, the numerical algorithm implemented was based on a minimization of the norm identifying the proximity of FE model and measured results in terms of the arrival time of wave propagation, as shown below.

$$J = \min_{x,y} \sum_{\omega} \sum_s \|T_{s,recorded}(\omega) - T_{s,FE}(\omega, x, y)\| \quad (4)$$

where $T_{s,recorded}$ – is the time of propagation as a function of frequency, as extracted from the raw sensor data; $T_{s,FE}$ – is the time of propagation as a function of frequency, as extracted from the FE simulation; x,y – unknown coordinates of the impact. Propagating flexural waves are naturally dispersive, whose velocities are a function of frequency ω . The function J is built by summation of the arrival time norms over all sensors, $s=1,2,\dots$ and over all frequencies ω picked for the data analysis.

Figure 9 illustrates the transient response of an elastic plate composed of 16 orthotropic plies, subject to the impact by a rectangular impulse load with duration time of 0.001 seconds. Figure 10 illustrates the 2-D wavelet transformation from the measured signal in the time – frequency domain, with corresponding contour lines. For each scale on this plot, the distance to the maximum peak indicates the arrival time of the wave group velocity. Note, that the arrival time of the group velocity from the simulation in Figure 9 is approximately 2.5 milliseconds and that matches the peak of the wavelet transform output as measured on the vertical time scale axis of Figure 10.

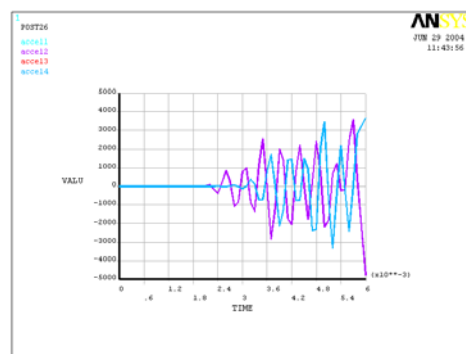
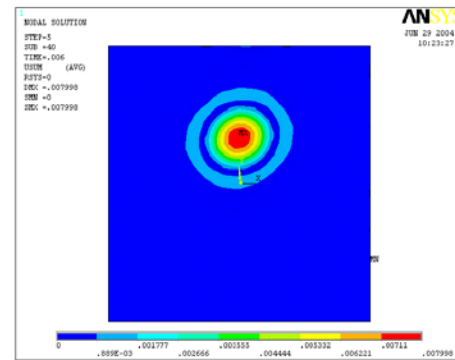


Figure 9 - FE-Based Transient Response under Impulse Load with Duration 0.001 sec

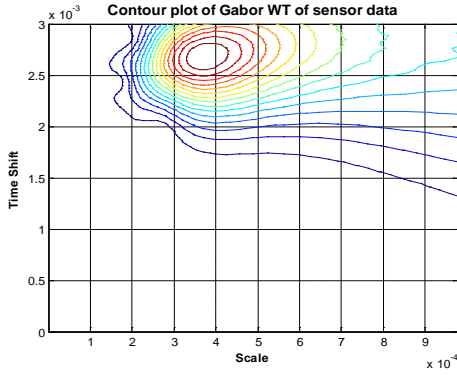


Figure 10 - Wavelet Transform of the Predicted Response

The main drawback from using this approach is that practical implementation of this model-based approach using the FE model dynamic transient solution are very CPU intensive. Hence, an additional method that directly utilizes the equations of motion for dispersive waves was also developed and is presented next.

Method 2: Dispersive Wave Equations of Motion in Laminated Composites

Impact detection localization is an inverse problem that can also be addressed based upon theoretical principles of dispersive wave propagation. Based on the Mindlin–Reissner shell theory, the relationships between the in-plane stress vector $N=(N_x, N_y, N_{xy})^T$, bending moments $M=(M_x, M_y, M_{xy})^T$, in-plane strains $\varepsilon=(\varepsilon_x, \varepsilon_y, \varepsilon_{xy})^T$, and curvature vector $\kappa=(\kappa_x, \kappa_y, \kappa_{xy})^T$ can be found using the equation below.

$$\begin{Bmatrix} N \\ M \end{Bmatrix} = \begin{bmatrix} A & B \\ B & D \end{bmatrix} \begin{Bmatrix} \varepsilon \\ \kappa \end{Bmatrix} \quad (5)$$

where, the sub-matrix A represents the extensional stiffness, B – bending extension stiffness, and D – bending stiffness are calculated by the summation of the stiffness matrices Q_k which represent all of the elementary plies across the thickness (Jones,1975).

$$A = \sum_{k=1}^N Q_k (Z_k - Z_{k-1});$$

$$B = \frac{1}{2} \sum_{k=1}^N Q_k (Z_k^2 - Z_{k-1}^2);$$

$$D = \frac{1}{3} \sum_{k=1}^N Q_k (Z_k^3 - Z_{k-1}^3)$$

Z_k – the transverse coordinate of the k-th layer.

In the case of harmonic wave propagation, in-plane displacements, u, v, normal to plane displacements w and normal angle rotations ψ_x, ψ_y take the form

$$(u, v, w, \psi_x, \psi_y) = (U, V, W, \Psi_x, \Psi_y) e^{i(k_x x + k_y y - \omega t)} \quad (6)$$

Making the substitution into the equation of motion yields the following generalized Hermitian eigenvalue problem

$$\begin{bmatrix} K_{11} & K_{12} & K_{13} & K_{14} & K_{15} \\ K_{12} & K_{22} & K_{23} & K_{24} & K_{25} \\ K_{13} & K_{23} & K_{33} & K_{34} & K_{35} \\ K_{14} & K_{24} & -K_{34} & K_{44} & K_{45} \\ K_{15} & K_{25} & -K_{35} & K_{45} & K_{55} \end{bmatrix} - \omega^2 \begin{bmatrix} \rho h & 0 & 0 & 0 & 0 \\ 0 & \rho h & 0 & 0 & 0 \\ 0 & 0 & \rho h & 0 & 0 \\ 0 & 0 & 0 & \rho h^3/12 & 0 \\ 0 & 0 & 0 & 0 & \rho h^3/12 \end{bmatrix} \begin{Bmatrix} U \\ V \\ W \\ \Psi_x \\ \Psi_y \end{Bmatrix} = \begin{Bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{Bmatrix} \quad (7)$$

Where ρ is the mass density, h is the thickness of the plate, K – stiffness matrix of laminate, and ω - frequency of the wave. Once ω as a function of k_x and k_y is known, the phase and group velocities are determined using the relations;

$$C_p = \omega/k; \quad C_g = d\omega/dk; \quad k = \sqrt{k_x^2 + k_y^2}; \quad \theta = \arctan(k_y / k_x)$$

The objective is to extract the group velocity Cg as the function of frequency ω and direction of propagation θ . Based on these equations, the dimensionless group velocities, corresponding to different angles as a function of frequencies, are plotted in Figure 11.

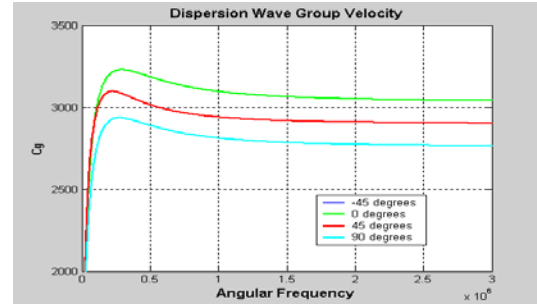


Figure 11 - Group velocity as functions of angular frequency and direction of propagation

Once the group velocity is known as a function of frequency and angular of propagation, and the wave arrival time to each sensor is extracted from the corresponding sensor transient record, one can determine the coordinates of the location based on the following algorithm.

The relation between time of arrival t and unknown coordinates x, y of the impact is given by the simple mechanics based nonlinear expression below.

$$t_i(\omega) = t_{delay}(\omega) + \frac{\sqrt{(x - x_{sensor,i})^2 + (y - y_{sensor,i})^2}}{V_g(\omega, \theta)} \quad (8)$$

where $t_i(\omega)$ – time of propagation of the dispersive wave, corresponding to the angular frequency ω , from the point of impact to the i-th sensor; x,y – the unknown coordinates of the

impact; x_{sensor} , y_{sensor} – the coordinates of the current sensor; $V_g(\omega, \theta)$ – group velocity as a function of frequency and direction of propagation, given by dispersive wave theory; $t_{\text{delay}}(\omega)$ – delay time, associated with the unknown local 3D and non-linear effects, as well as local damage phenomena. Three unknown variables are introduced into the equation above: two coordinates x, y and a delay time. For the number of measurements, this equation is satisfied in terms of the best fit, based on the least square approach.

5. EXPERIMENTAL TEST BED AND RESULTS

A flat, quasi-isotropic composite plate was used as a test bed for validating the proposed impact damage detection and isolation approaches. The objective was to assess the developed methodologies using acceleration-based sensors with the purpose of identifying (a) damage initiation and location in a composite structure. The combined data-driven and model-based approaches utilize analysis of wave characteristics (frequency, amplitude, velocity, type and damping characteristics) and source location using triangulation methods (in conjunction with time of arrival information and energy amplitude of signal received).

The material investigated is IM7/5250-4, quasi-isotropic $[0/45/90/-45]_{2s}$ laminate having the following elastic properties (x - y is in-plane while z is the thickness direction): $E_x=E_y=9.15$ Msi, $E_z=1.5$ Msi, $G_{xy}=3.49$ Msi, $G_{xz}=0.5$ Msi, $\nu_{xy}=0.32$, $\nu_{xz}=0.45$

The composite plate was simply supported (on wood panel) on two edges, as shown in Figure 12(a). Four accelerometers were mounted in the locations CH1, CH2, CH3, and CH4, as shown in Figure 2-12(b). The plate was then tapped with a hand held hammer at several

different chosen locations, and measurements were made at all four accelerometers. The data set was investigated to relate the basic signal characteristics to laminate properties in absence of damage and provides the training set for developing the methodology for source location.

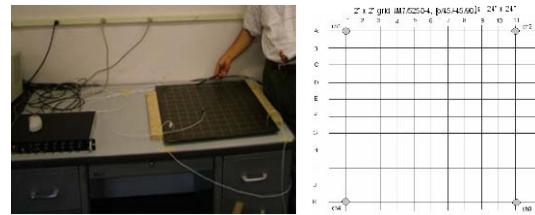


Figure 12 - Composite Plate Showing Support Conditions, and Location of Accelerometers

A total of 12 different locations were selected on the composite plate for tapping measurements. The identities of tapping locations for 5 measurements were kept secret while that of the remaining 7 were disclosed for training the algorithms. Figure 13 is a comparison of the predictions using the feature-based intelligent approach and model-based FE approach with the truth data for the 5 blind test cases.

Using the data-driven (feature-based) approach, an exact prediction was obtained for one of the tests and was within 1 grid spacing for the remainder tests. For the model-based approach, the prediction was within 1 grid space for one test, within 2 grid spaces for three of the tests and within 3 grid spaces for the final test. As seen in this figure, both approaches are reasonably good in predicting the location of the impact using the measurements from the accelerometer sensors.

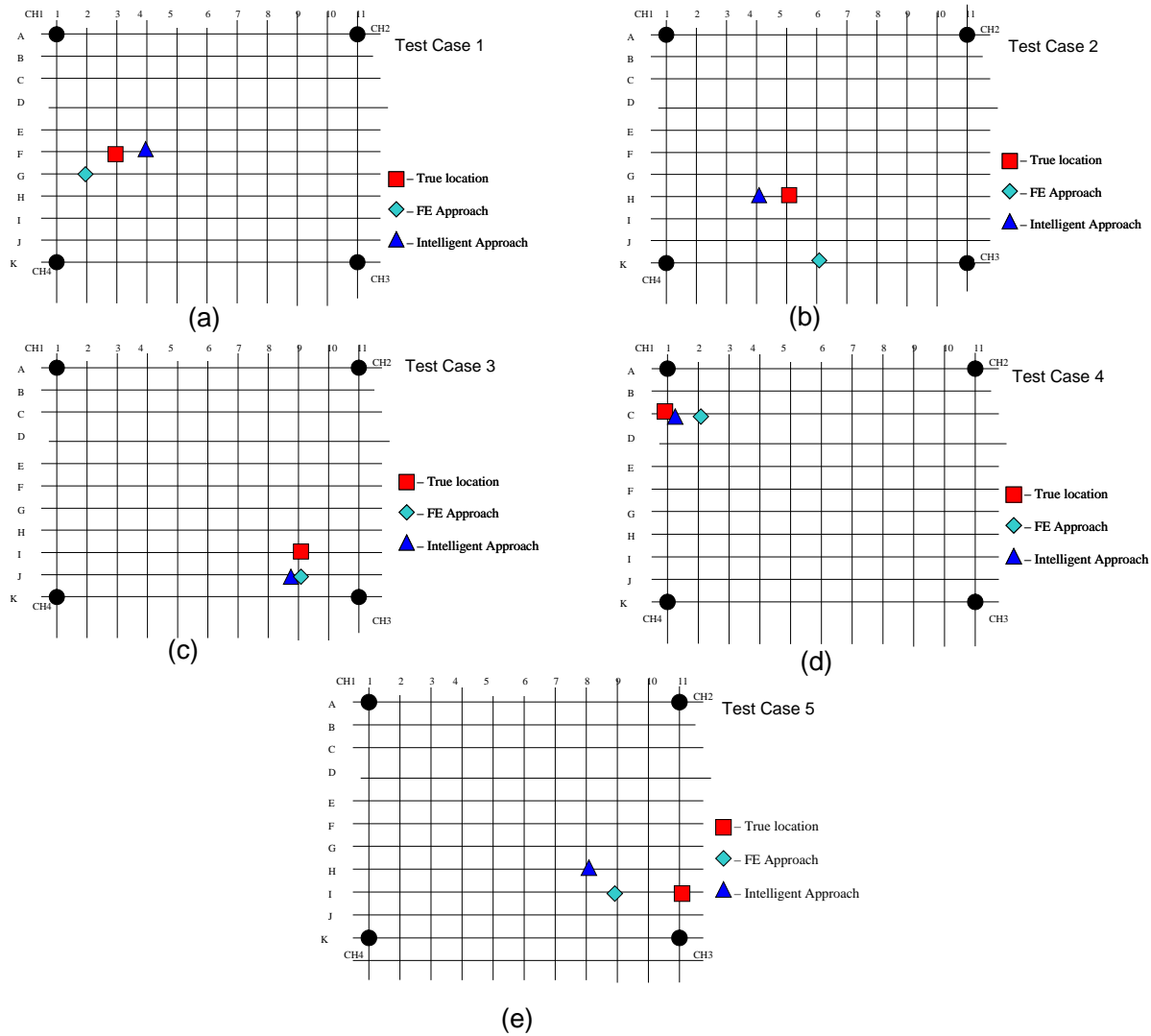


Figure 13 - Comparison of Predictions Using Model-Based and Feature Based Approaches

6. CONCLUSIONS

Impact damage, which may occur during service or be maintenance induced, is a leading cost driver for composite structures used in various aerospace vehicle applications. Impact Technologies, in collaboration with the University of Dayton Research Institute (UDRI), have developed both feature-based and model-based impact damage detection and localization algorithms for composite structures. Specifically, this paper presented: 1) A robust and low-cost sensing approach using only COTS accelerometers to provide comprehensive insight into the structure's health state; 2) Advanced signal analysis and feature extraction techniques that included time-frequency based wavelet transforms and higher order statistics; 3) An intelligent approach for impact damage localization using triangulation and neural network techniques; 4) Two different model-based impact damage detection techniques; and 5) Experimental validation of the proposed algorithms using a composite plate test bed.

Although these results are considered preliminary, our research team believes that the robust nature of the sensors and algorithms will allow for future scalability to larger and more complex structures.

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BIOGRAPHIES



Dr. Michael J. Roemer is the Director of Engineering at Impact Technologies in Rochester, NY and Adjunct Professor of Mechanical Engineering at the Rochester Institute of Technology. He was formerly a Vice President of Engineering at STI Technologies prior to joining Impact Technologies. Mike has a Ph.D. in Mechanical Engineering, M.S. in Systems Engineering and B.S. in Electrical Engineering, all from the State University of New York at Buffalo. He has over 16 years experience developing real-time, automated health management technologies for complex systems, including large steam and gas turbines, gas turbine engines, rotary/fixed-wing aircraft subsystems and naval propulsion systems. He has developed several diagnostic and prognostic capabilities for complex systems utilizing probabilistic methods that are directly linked to maintenance planning and system operation. He is the author or co-author of more than 50 technical papers in these subject areas. He is currently the Chairman of the Machinery Failure Prevention Technology (MFPT) Society, a Division of the Vibration Institute, and Prognostics Lead for the SAE-E32 Engine Condition Monitoring Committee.



Dr. Jianhua Ge is a Project Manager at Impact Technologies with over 14 years experience in fault tolerant control, signal processing, information fusion, decision aids, intelligent agents, prognostics and health management. He received a Ph.D. degree in Automation Alexander von Humboldt fellow at the Department of Electrical Engineering, Duisburg University, Germany. He was a Senior Engineering Specialist at American GNC Corporation. At Impact Technologies he is responsible for multiple SBIR/STTR projects on software agents for data-driven prognostics, software agents for airspace management and deconfliction of networked UAVs, and automated contingency Engineering from Zhejiang University, China. He was an management for UAVs and propulsion. Dr. Ge has published more than 30 papers in his areas of expertise