Adaptive SHM Methodology to Accommodate Ageing, Maintenance and Repair

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ABSTRACT

Structural Health Monitoring (SHM) systems are susceptible to rising false positive rates over time due to ageing materials, scheduled maintenance procedures and new structural repairs. The alternatives of, manually updating thresholds or re-training software are impractical, time-consuming and complicate certification. This paper discusses an adaptive SHM methodology to accommodate changes in structural response that are not attributable to damage. This methodology provides a path to implementing most standard damage detection algorithms, ranging in sophistication from percent change to pattern recognition, across an aircraft fleet in a static release format. The main departure from traditional SHM architectures resides in adaptive modules that can accommodate input changes, such as those due to manufacturing or installation variability, sensor health, bond quality and typical wear on a structure. The overall goal was to integrate these adaptive modules within standard algorithms and logic without impacting their underlying reasoning or validity. An application of this methodology is presented using data collected from graphite/epoxy laminates subjected to Lamb wave testing. In this example, a pattern-recognition algorithm is employed to provide information about the presence, type and severity of damage. The proposed methodology eliminates the need for re-training when slight variations are introduced to the experimental setup.

INTRODUCTION

Structural Health Monitoring (SHM) technology aims at the development of systems capable of continuously monitoring structures for damage with minimal human intervention to reduce life-cycle costs [1-2]. Researchers have developed numerous viable algorithms for characterizing structural damage using a variety of damage detection methods such as Lamb waves, modal analysis and Eddy currents to name a few [3-6]. The majority of these methods rely on experimental, or at the very least well simulated baseline, measurements to define the undamaged or pristine state of the structure. While these methods have yielded promising accuracy

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in laboratory conditions, traditional algorithms are susceptible to rising false positive rates over time due to ageing materials, scheduled maintenance procedures and new structural repairs [7-8]. In addition, slight differences between aircraft in a fleet, such as those due to sensor placement, bondline preparation and manufacturing tolerances, could have a significant adverse effect on accuracy as well. Ideally, these issues could be overcome by revising algorithms, manually updating threshold levels or re-training software for individual aircrafts continuously over time, however this solution is logistically impractical as well as extremely time consuming, potentially negating the original benefits of deploying an SHM system. Furthermore, tailored changes to algorithms could invalidate or at lease complicate the certification of an SHM system. This paper discusses an adaptive SHM methodology to accommodate perturbations in structural response not attributable to damage, while maintaining or accounting for algorithm accuracy. Results are presented for simulated perturbations introduced to experimental data collected from composite plates subject to Lamb wave tests and pattern recognition.

ADAPTIVE METHODOLGY FOR SHM ALGORITHMS

The overall goal of the present research was to integrate adaptive modules within standard algorithms and logic without impacting their underlying reasoning or validity. This methodology provides a path to implementing most typical damage detection algorithms, ranging in sophistication from percent change to pattern recognition, across an aircraft fleet in a static-release format. The following paragraphs describe four flowcharts developed to implement this methodology.

The Standard Training Flowchart, seen in **Figure 1**, indicates the steps necessary to calibrate a generic SHM algorithm, essentially characterizing the definitions for various states. A more thorough discussion can be found in a previous paper, however generally training input consisting of data linked to complementary damage state is iterated through a series of signal processing steps to establish the training output parameters to be locked and used for testing [9]. A separate set of validation input is also utilized to establish state confidence levels. The Standard Testing Flowchart, seen in **Figure 2**, is executed to determine the present state of a structure given the training output parameters. Beyond the acquired test data, only an undamaged baseline from the test structure is required to apply the previously developed algorithms and calculate prediction accuracy.

The Adaptive Training Flowchart, seen in **Figure 3**, is the main departure from traditional SHM architectures. Adaptation modules at the signal and feature level are established using perturbed training input and baseline signals (experimentally or simulation derived) iterated through the Standard Testing Flowchart, with the goal of minimizing impact on the algorithm accuracy. These adaptation parameters are also locked to be used for adaptive testing along with updated confidence levels for each state as a function of perturbation level. Finally, Adaptive Testing Flowchart, seen in **Figure 4**, is executed similarly to the standard test procedure to determine the state of damage including the adaptation parameters. Here, beyond the original baseline, a signal from a future “known good state” can be used to accommodate signal perturbations through the adaptation modules.

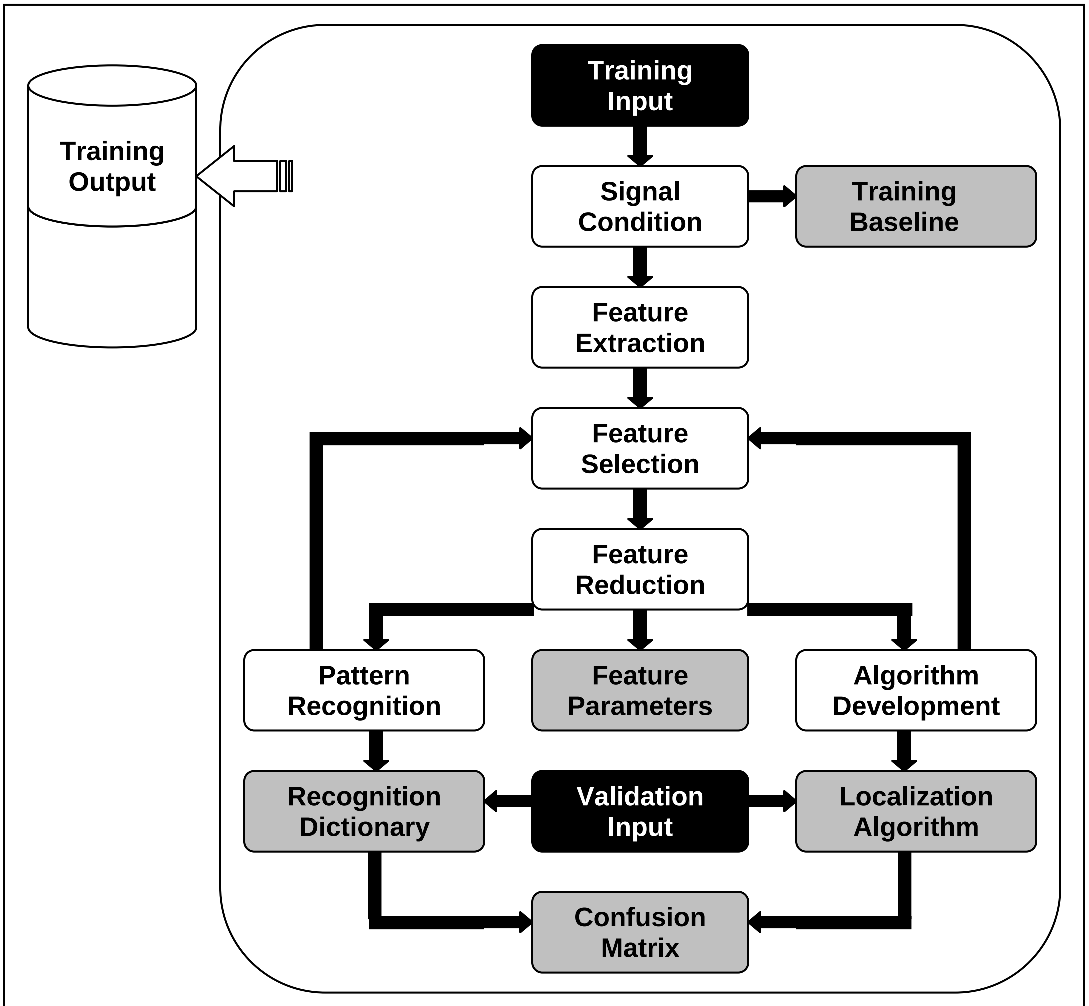

Figure 1: Training Flowchart used to derive optimized damage characterization algorithm

<u>Training Flowchart Input</u>
Training Input – voltage versus time data linked to damage presence, type, size and location info
Validation Input – separate set identical to training input used to validate generated algorithms

<u>Iterative Functional Blockset</u>
Signal Condition – signal processing tools to remove unwanted artifacts, filter and de-noise data
Feature Extraction – extracts quantifiable features from time, frequency and energy domains to characterize signal (max amplitude, arrival time, peak frequency, etc.)
Feature Selection – most discriminative features are down-selected, such as those that are most consistent within a particular class and most variable between classes
Feature Reduction – techniques to reduce the dimensionality of the selected features
Pattern Recognition – models used to associate test data with a pre-trained classification
Algorithm Development – equations to determine distance to damage based on time of flight

<u>Training Output</u>
Feature Parameters – designates selected features to extract and appropriate reductions
Training Baseline – defines statistical average for all undamaged structure
Recognition Dictionary – defines pattern recognition state machines
Localization Algorithm – compiled algorithm to determine distance to damage
Confusion Matrix – table of statistical accuracies of algorithms applied to validation data

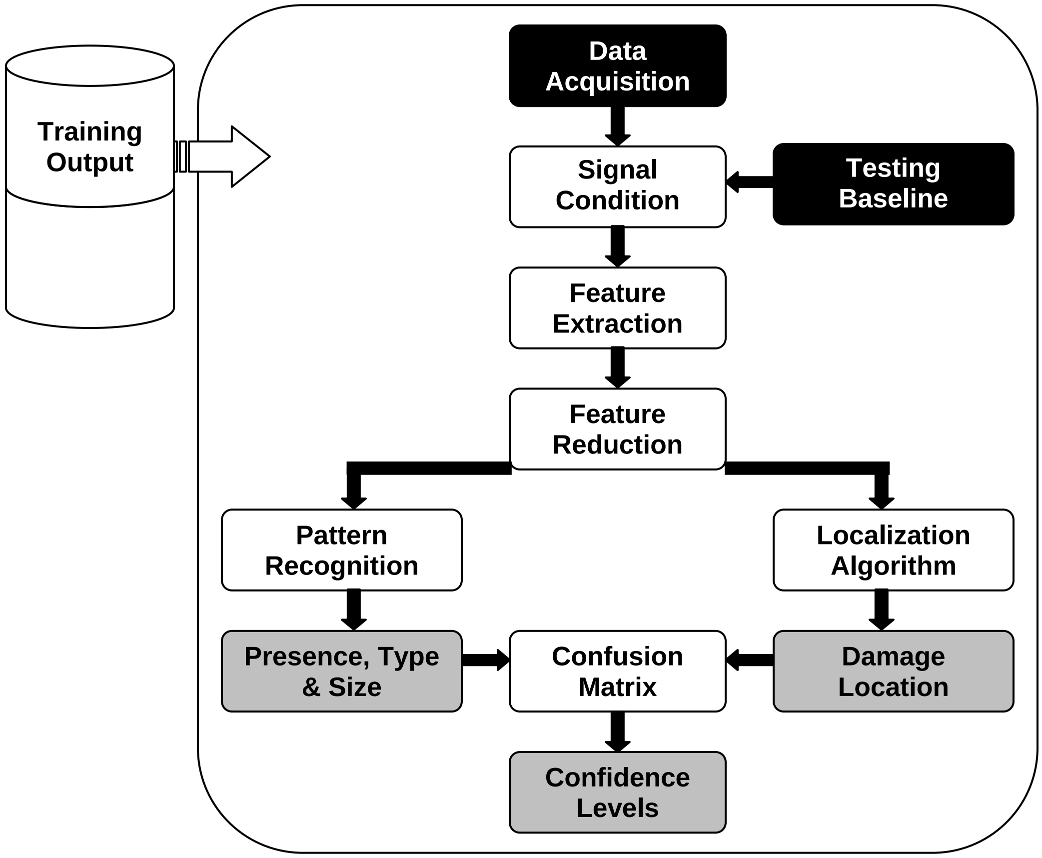

Figure 2: Testing Flowchart

<u>Testing Flowchart Input</u>
Data Acquisition – raw voltage versus time data is acquired from sensors
Testing Baseline – undamaged baseline signal taken from test structure prior to testing
Training Output – parameters generated by the Training Flowchart govern the testing algorithms

<u>Functional Blockset</u>
Signal Condition – filtering and denoising pre-set in Training Flowchart
Feature Extraction – extraction of selected features optimized in Training Flowchart
Feature Reduction – reduction of feature dimensionality pre-set by Training Flowchart
Pattern Recognition – using the recognition dictionary from the Training Flowchart
Localization Algorithm – using the algorithms generated in the Training Flowchart
Confusion Matrix – matrix generated using validation input is used to assign confidence levels

<u>Testing Output</u>
Presence of Damage – pattern recognition determines presence of damage above threshold value
Type of Damage – pattern recognition determines type of damage or “unknown” class
Size of Damage – pattern recognition determines severity of damage within pre-set ranges
Location of Damage – time of flight algorithm determines approximate location of damage
Confidence Levels – validated confusion matrix yields confidence levels for each damage state

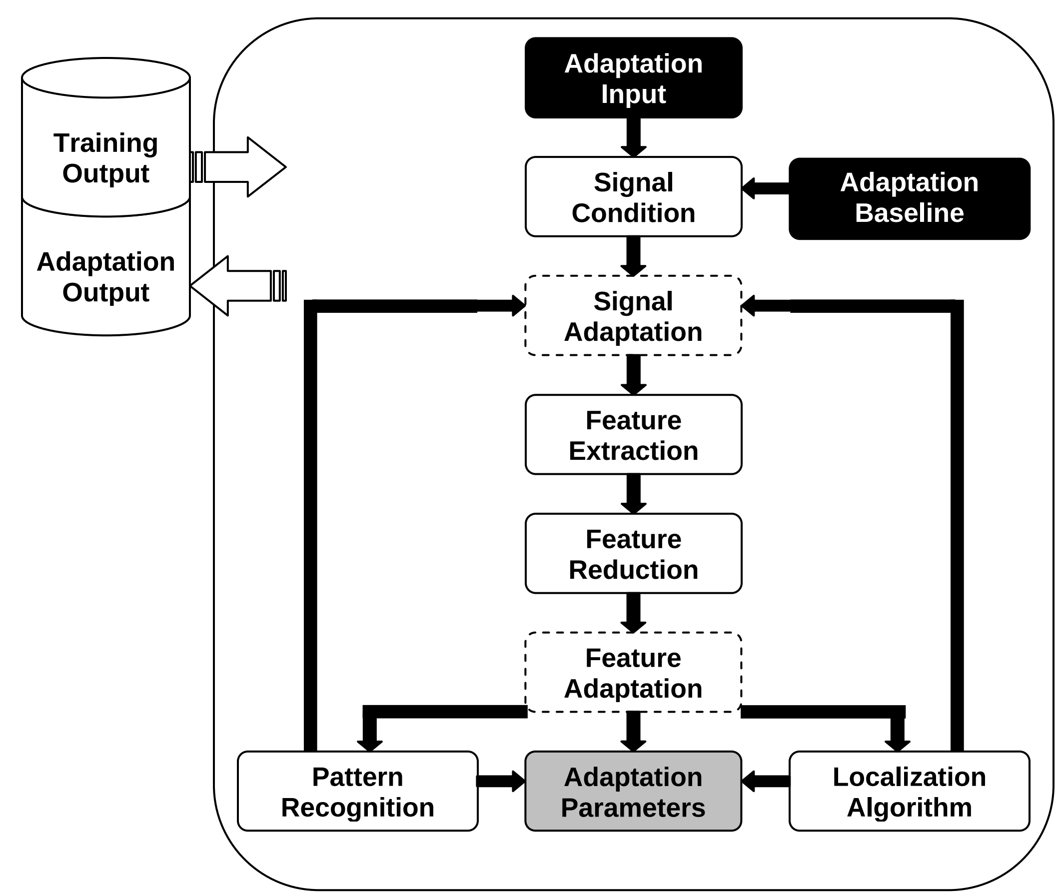

Figure 3: Adaptive Training Flowchart

Adaptive Training Flowchart Input
Adaptation Input – similar in format to training data, includes multiple sets of perturbations
Adaptation Baseline – set of perturbed baselines that complement the Adaptation Input
Training Output – parameters generated by the Training Flowchart govern the testing algorithms

Standard Functional Blockset
Signal Condition – filtering and denoising pre-set in Training Flowchart
Feature Extraction – extraction of selected features optimized in Training Flowchart
Feature Reduction – reduction of feature dimensionality pre-set by Training Flowchart
Pattern Recognition – using the recognition dictionary from the Training Flowchart
Localization Algorithm – using the algorithms generated in the Training Flowchart

Iterative Adaptive Blockset
Signal Adaptation – signal is manipulated to resolve perturbations from training baseline
Feature Adaptation – features are manipulated to resolve perturbations from training baseline

Adaptation Output
Adaptation Parameters – optimized parameters for signal and feature adaptation
Adaptation Matrix – table of statistical accuracies of algorithms applied to adaptation data

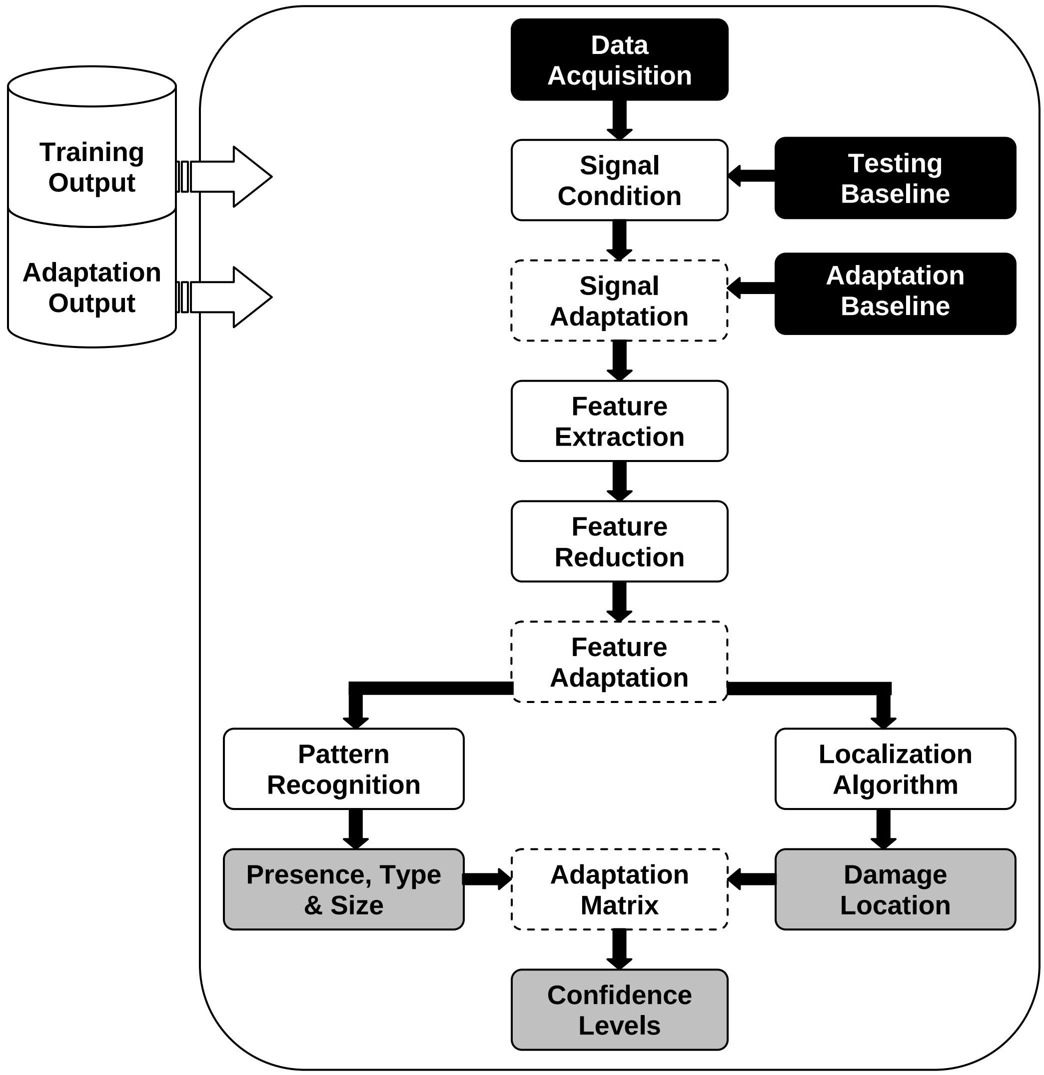

Figure 4: Adaptive Testing Flowchart

<u>Adaptive Testing Flowchart Input</u>
Data Acquisition – raw voltage versus time data is acquired from sensors
Testing Baseline – original undamaged baseline signal taken from test structure prior to testing
Adaptation Baseline – perturbed baseline signal to be used for adaptive algorithms
Training Output – parameters generated by the Training Flowchart govern the testing algorithms
Adaptation Output – parameters generated by Adaptive Training Flowchart govern adaptation

<u>Standard Functional Blockset</u>
Signal Condition, Feature Extraction & Reduction, Pattern Recognition and Localization Algorithm all remain locked as pre-set in Training Flowchart

<u>Iterative Adaptive Blockset</u>
Signal & Feature Adaptation remain locked as pre-set in Adaptive Training Flowchart
Adaptation Matrix – confusion matrix from Adaptation Output used to assign confidence levels

<u>Testing Output</u>
Damage Presence, Type, Size & Location – from pattern recognition & localization algorithms
Confidence Levels – adaptation confusion matrix yields confidence levels for each damage state

ADAPTATION MODULES

To compensate for small perturbations in signals, adaptation modules have been developed. If the original baseline signals obtained from a pristine structure is B_O and an updated baseline signal from the same structure obtained at a later time is designated B_N, then the main function of the adaptive compensation modules can be viewed as transforming B_N to B_N' such that $B_N' \cong B_O$. This takes place with the two underlying assumptions that B_N is collected within a known no-damage condition, and that the differences between B_O and B_N are within some tolerable threshold. This compensation occurs as a two-step process, first at the signal level and then at the feature level. At the signal level, adaptation is an extension of the signal conditioning step. The main difference is that most of the conditioning parameters for B_N are determined with reference to the original baseline signal B_O. In this step signal normalization $B_N' = T_N * B_N$ was achieved using the normalizing vector T_N:

$$T_N = \frac{1}{\max(B_{N-peak-to-peak})} \qquad 1$$

At the feature level, the B_N feature vector F_{BN} is transformed to F_{BN}' by a series of transformation vectors, T_R for Rotation, T_S for Scaling, and T_R for Translation:

$$\overrightarrow{F_{BN}}' = (T_S * T_T * T_R) * \overrightarrow{F_{BN}} \qquad 2$$

Transformation vectors are computed using the following optimization relations, where F_{B0} is the feature vector derived from the original baseline signal B_O.

$$\min\left(\left|\overrightarrow{F_{B0}} - T_x \overrightarrow{F_{BN}}\right|\right),\ X \in \{S, T, R\} \qquad 3$$

Computed transformation vectors are then applied to any signal recorded thereafter.

SIMULATED VALIDATION OF ADAPTIVE METHODOLGY

An application of this methodology is presented using data collected from 9 - 0.1”x11.75” square quasi-isotropic graphite/epoxy laminates with progressively severe levels of hole, delamination and impact damage being introduced. Each plate contained 2 bonded sensor nodes, and was subjected to Lamb wave testing [10-12]. Prior work applying a pattern-recognition algorithm to this data demonstrated 100% accuracy in determining presence and type of damage across 9000 trials, and 78% accuracy in predicting severity [9, 13-14]. These results were obtained using real data following the standard Training and Testing Flowcharts.

To achieve first-order validation of this adaptive methodology, simulated perturbations were introduced into the experimentally collected baseline and test signals, and subsequently the Adaptive Training and Testing Flowcharts were executed. First, a time delay between 0-100μs was introduced, representing a change introduced by a repair moving a boundary condition. Next, a uniform amplitude attenuation between 0-10% was introduced, replicating a degraded sensor bondline. Last, a central frequency shift between 0-10% was introduced, as seen in aging or from saturated microcracks reducing the bulk material modulus within a design allowable range. Results presented in **Figure 5** demonstrate the effect of adaptation on the accuracy of predicting damage presence for perturbed signals.

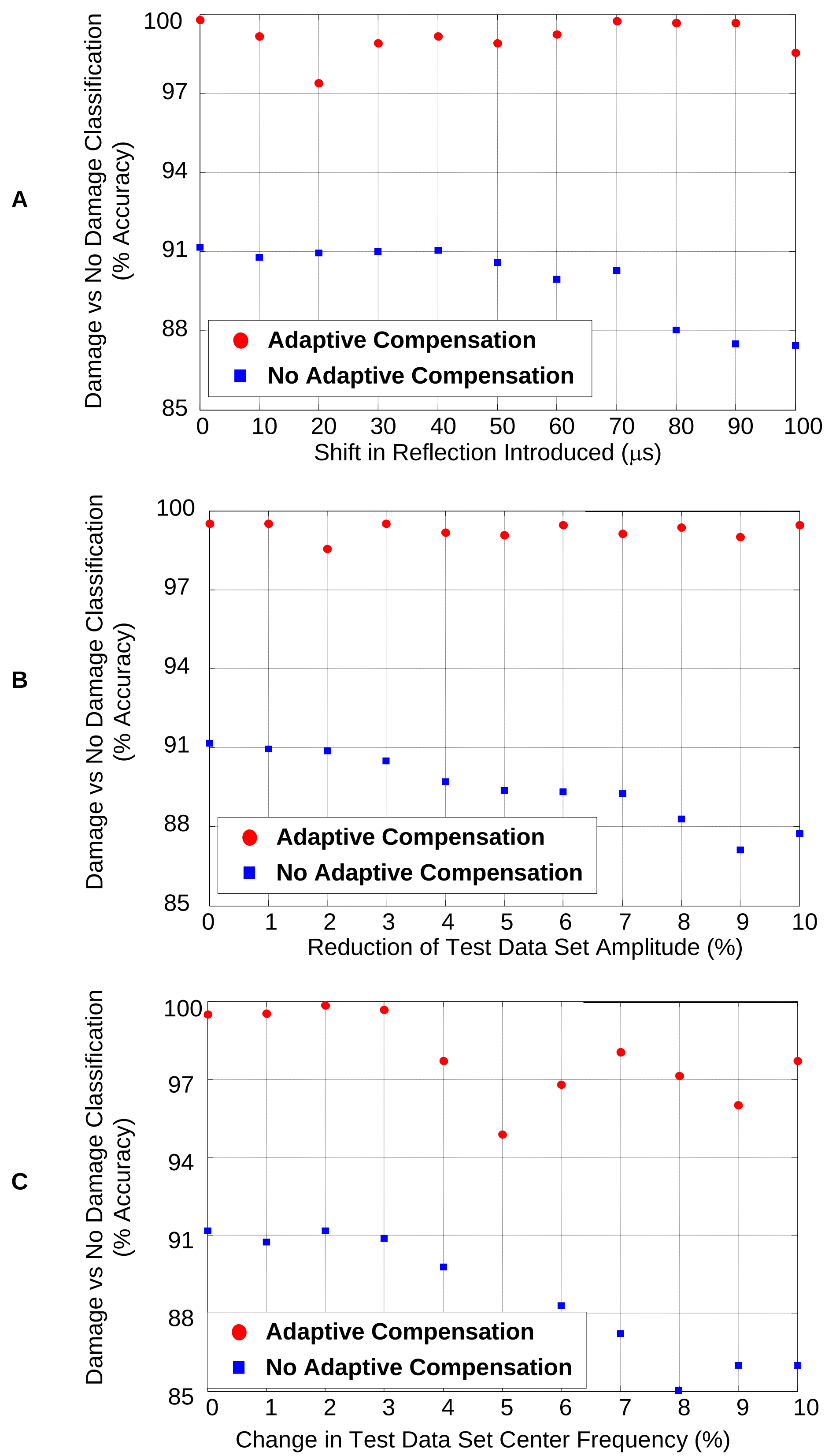

Figure 5: Results demonstrating effect of simulated signal perturbation on a pattern recognition algorithm with & without adaptive compensation: A) time, B) energy, & C) frequency domains

CONCLUSIONS

This paper presents an adaptive SHM methodology, designed to maintain damage detection algorithm accuracy while accommodating signal perturbations caused by ageing materials, scheduled maintenance procedures and new structural repairs. The methodology consists of three flowcharts for training of standard algorithms, training of the adaptation modules and testing using these trained parameters. Adaptation modules are inserted at both the signal and feature level to transform the test signal based on differences between original and present baseline signals. Results are presented for detecting the presence of damage in composite plates with simulated perturbations of up to 10% in the signal time, energy and frequency domains. The standard pattern recognition algorithm exhibited reduced accuracy due to the perturbations, which further decreased as greater signal change, while the algorithm with adaptive compensation maintained accuracy by incorporating the new baseline signal. The present research was successful in demonstrating the feasibility of using adaptive modules to compensate for signal perturbations not attributable to damage, however work remains to fully develop this methodology for commercial applications. Future work will aim at conducting experiments to optimize the methodology, examine effects of signal perturbation on damage type, severity and location, as well as validation beyond pure simulation.

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