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Adaptive SHM Methodology to Accommodate

Structural Ageing, Maintenance and Repair

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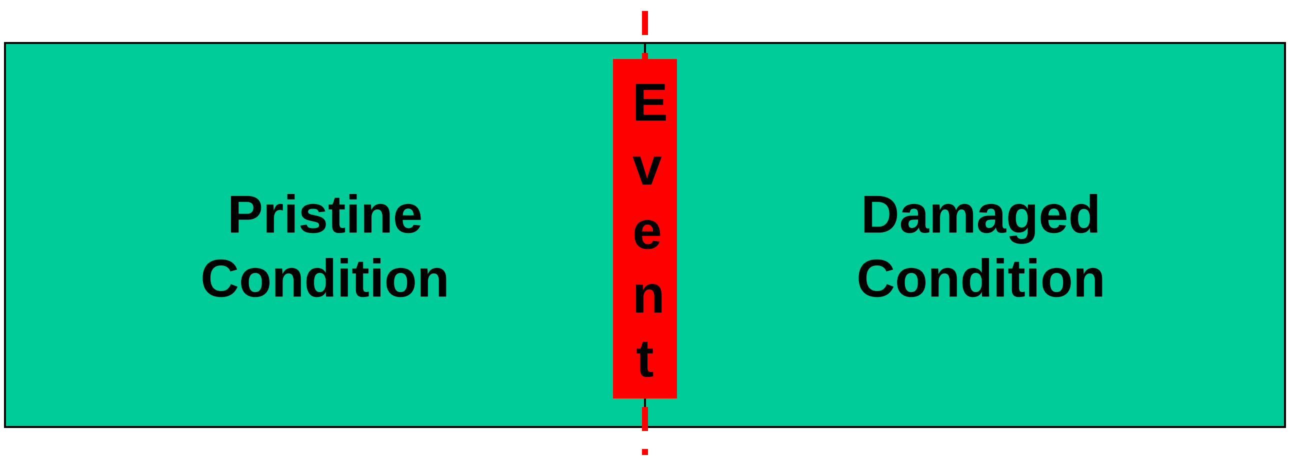
Introduction

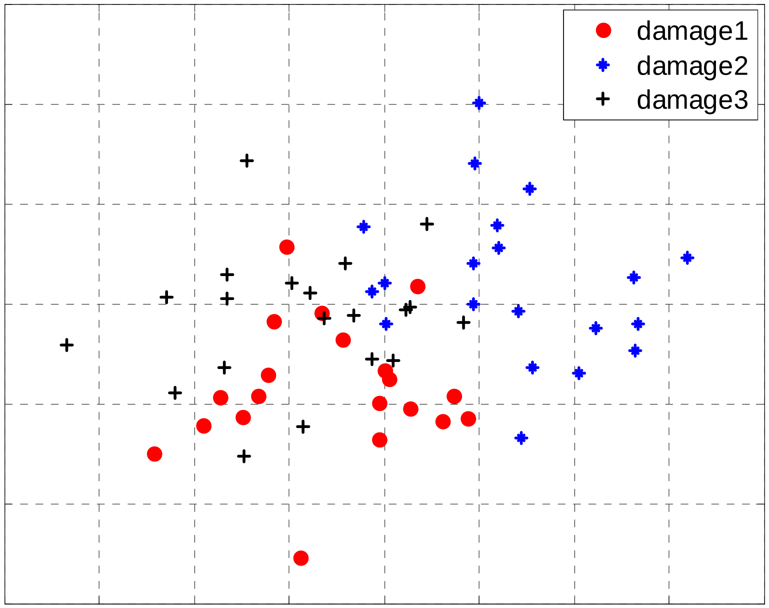
- SHM algorithms are susceptible to rising false positive rates
  - materials age due to environmental and mechanical fatigue
  - maintenance and repairs can tighten bolts, replace ribs or add patches
- Differences between aircraft in a fleet could affect accuracy
  - sensor tolerances, placement, installation and bond preparation
  - manufacturing tolerances for individual aircraft
- Can compensate by revising or retraining algorithms over time
  - logistically impractical, time consuming, negates SHM economic benefits
  - tailored changes invalidate/complicate certification of an SHM system
- Adaptive pattern recognition-based methodology proposed
  - accommodate perturbations in structural response not due to damage
  - goal of maintaining or accounting for algorithm accuracy

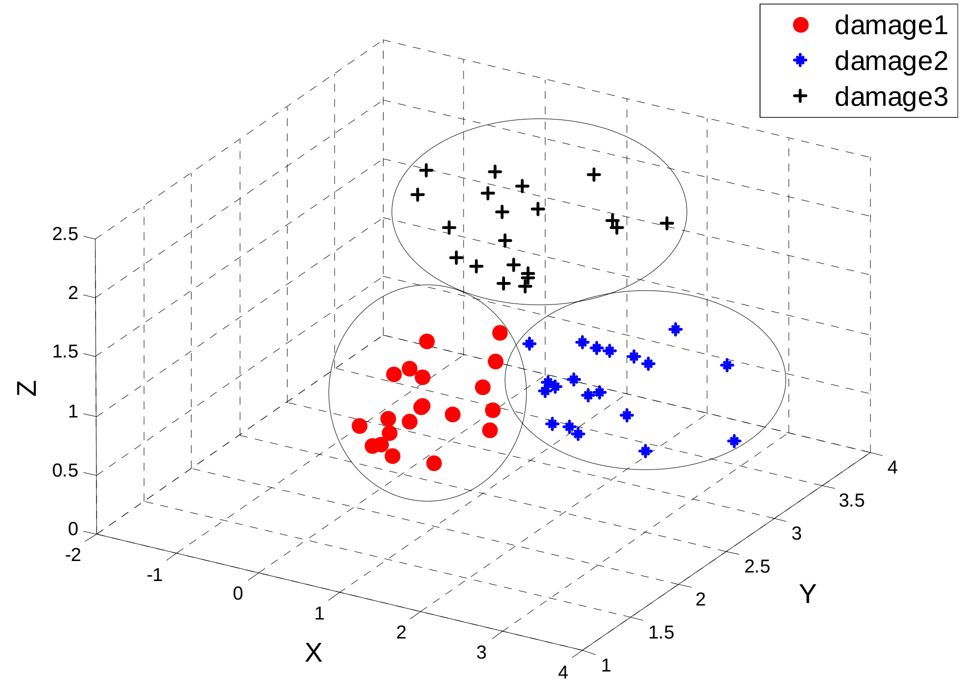
Damage Detection Fundamentals

- Several challenges involved in detecting damage
  - metals: corrosion and fatigue cracks primary concern
  - composites: delamination and impact (below visible surface) dominate
  - modes may not be discrete, can interact for both materials
- Ideally top-level binary categorization of pristine or damaged
  - taking micromechanics view materials inherently have flaws
  - microscopic flaws grow slowly, accelerated overload or impacts events
  - damage threshold must be defined for some detectable flaw size level



State Classification

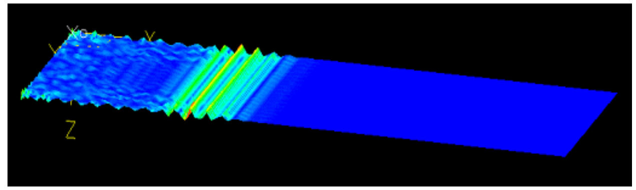


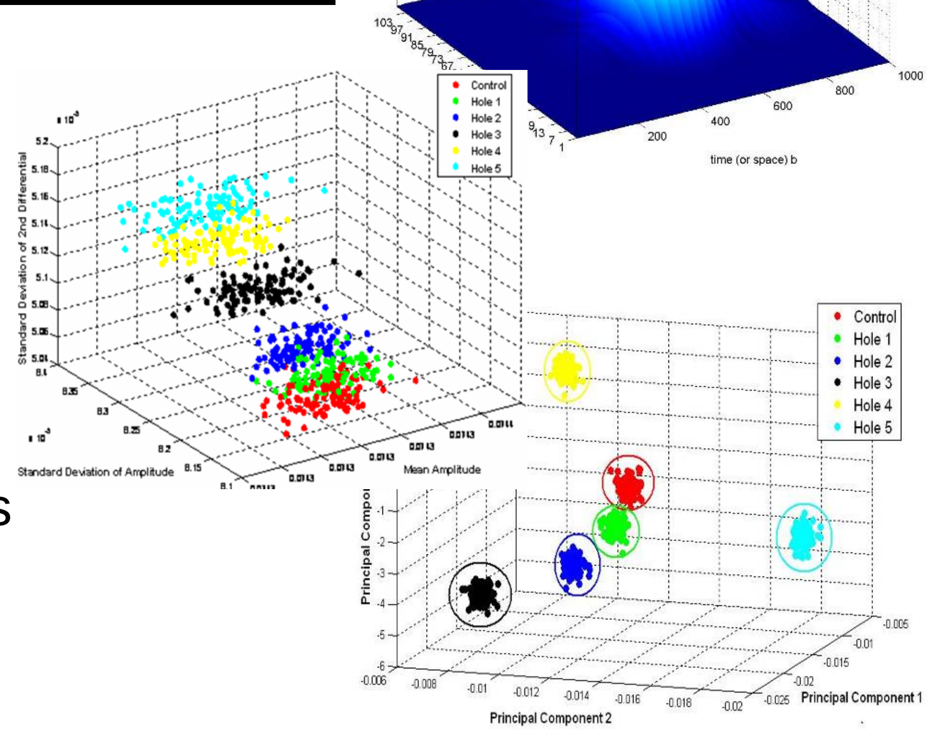


- Would like further classification beyond presence of damage
  - limited features may be used to separate damage and no damage
  - may not be feasible to distinguish between modes if linearly inseparable
- Must extract many separate features for detailed classification
  - pattern recognition methods trained to recognize multiple damage states
  - large feature set may lead to redundancy and computational inefficiency
  - feature reduction techniques can be employed to reduce dimensionality

Standard Methodology Steps

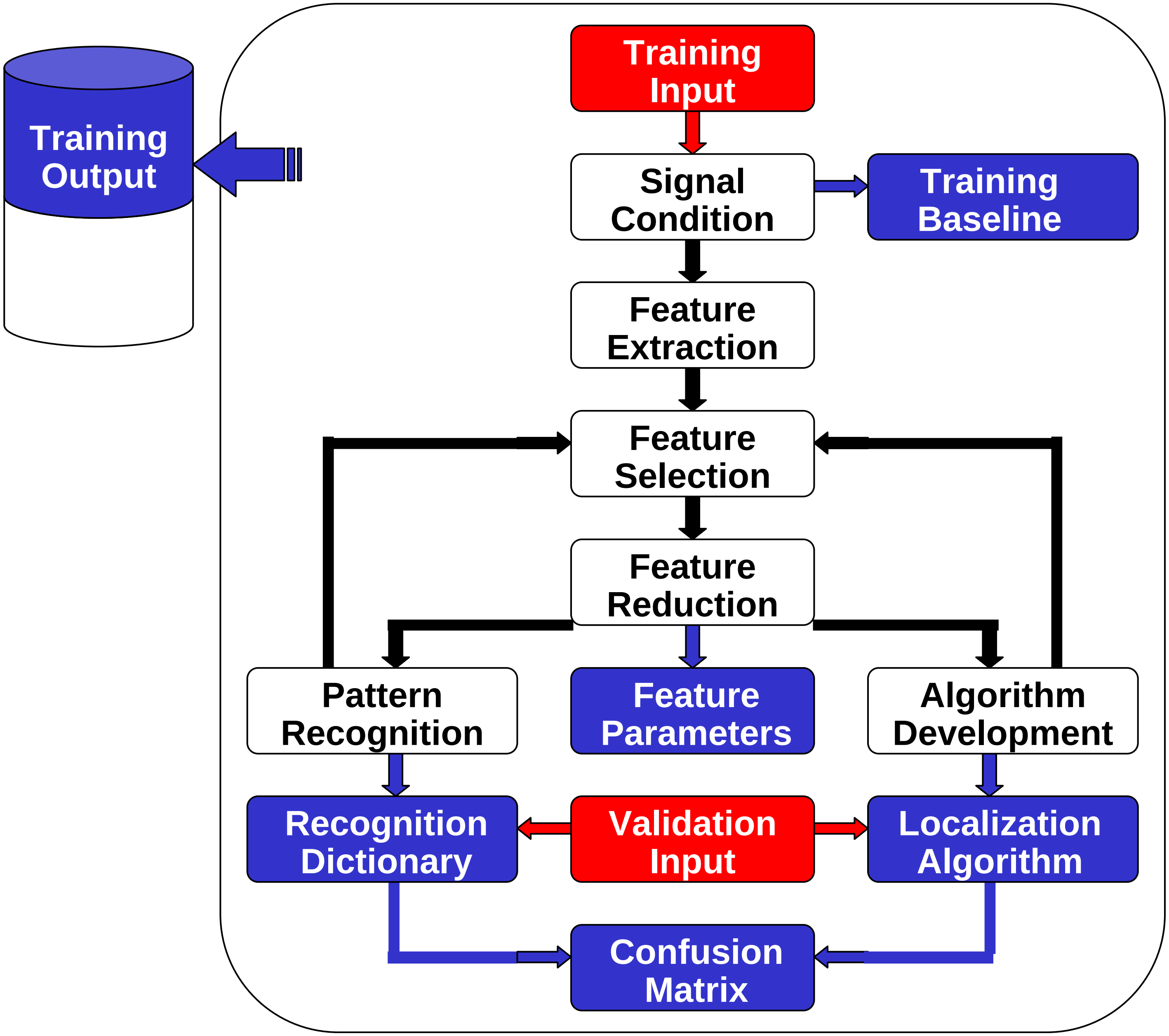
- Signal Conditioning
  - denoise raw signal
  - remove unwanted artifacts



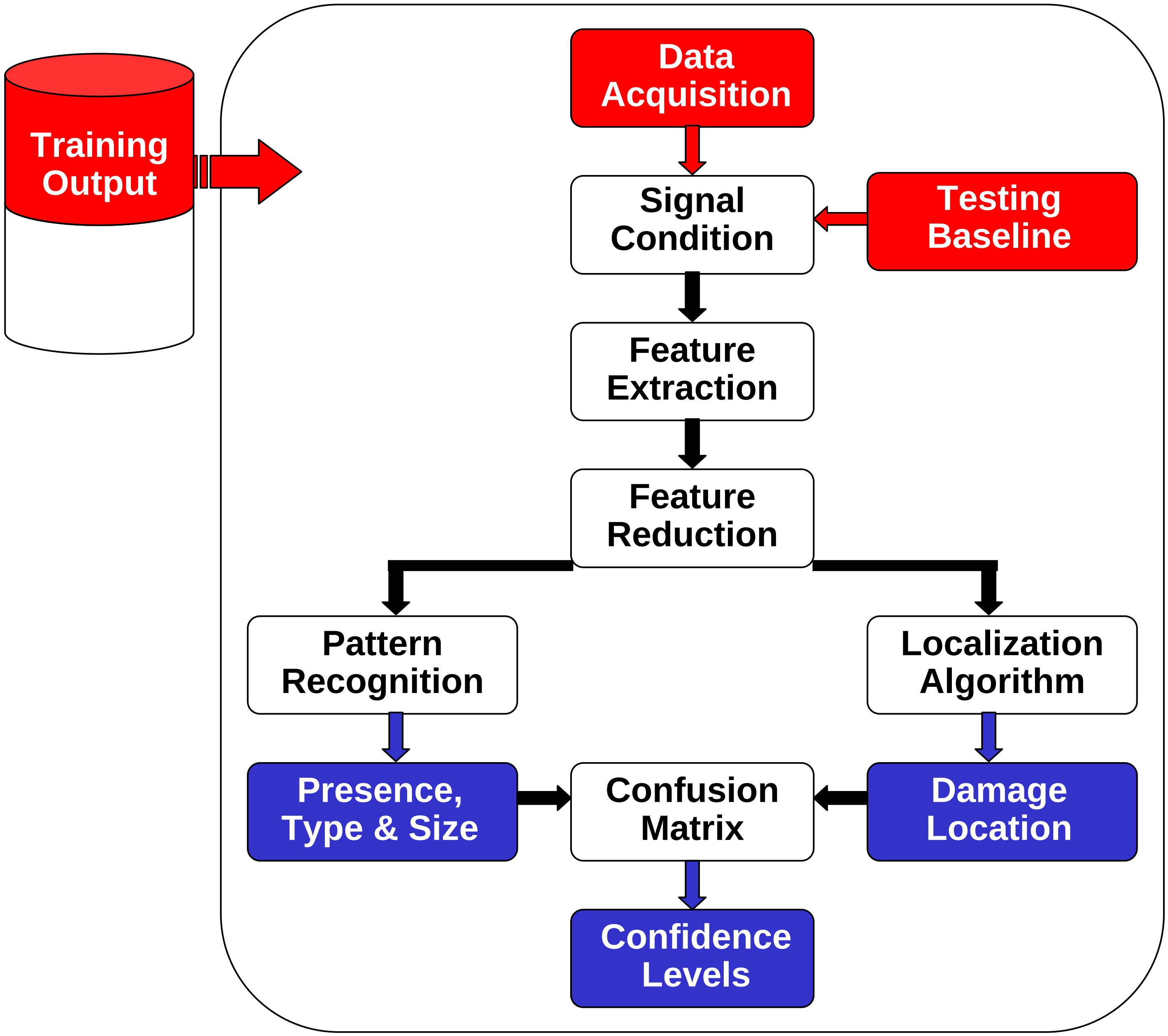


- Feature Extraction
  - discriminative features for analysis
  - time, frequency & energy domains
- Feature Selection
  - repeatable features unique to class
  - can reduce dimensionality (PCA)
- Algorithms
  - Pattern Recognition (PR) to identify damage presence, type and severity
  - localization performed with convention single or multi-sensor methods
  - confusion matrix can be used to calculate confidence levels

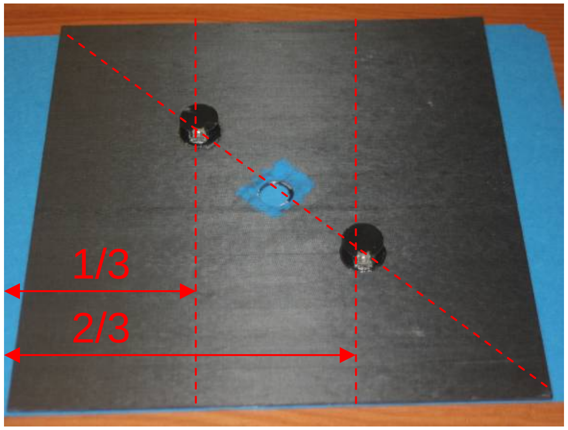
Standard Training Flowchart



Standard Testing Flowchart



Experimental Setup

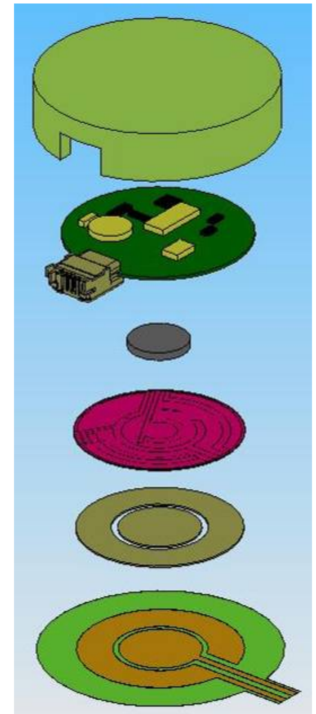


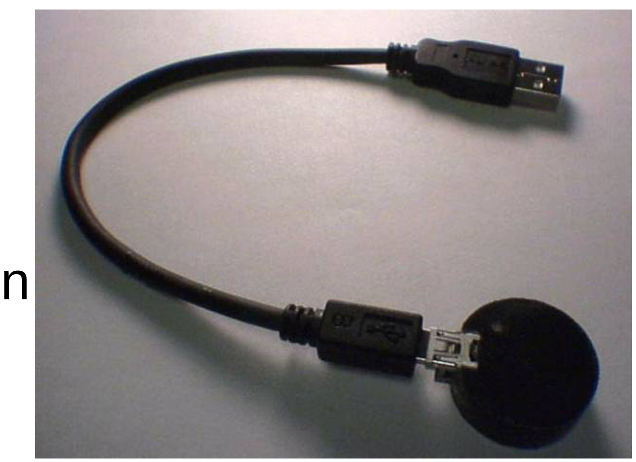
Plates	Damage Type	Damage Severity
3	Impact (5 lbs dropped weight)	4”, 8”, 16”, 32”
3	Hole (center drilled)	$^{1}/_{32}$”, $^{1}/_{8}$”, ¼”, ½”
3	Delamination (corner cut)	¼”, ½”, 1”, 1.5”

- 11.75” x 0.1” square quasi-isotropic CFRP laminates, 2 nodes
- Lamb wave tests performed in pulse-echo mode at 100kHz
- 3 damage modes investigated with 4 levels of severity for each
- 100 tests per node for each configuration, total 9000 data sets
  - 1 node for each damage type was designated as the “training node” and all data collected was used to train PR algorithm
  - other nodes on same and all separate plates were “testing nodes” used to collect experimental data for subsequent predictions

M.E.T.I.-Disk 3 Digital SHM Nodes

- Monitoring & Evaluation Technology Integration
  - concentric piezoceramic sensor/actuator elements
  - rigid-flex technology used for ADC & DAC
  - mini-USB connector for power and data transfer
  - 1” diameter urethane encapsulation for durability
- Digital SHM infrastructure (TRL 7 demonstrated)
  - Lamb wave, modal analysis, AE capable
  - 2 channel 1MHz 16-bit ADC & 1MS/s 8-bit DAC
  - 20Vpp drive voltage, programmable gains
  - daisy-chain compatible using CAN bus
- Point-of-Measurement (POM) sensing
  - RAM enables local filtering, logic & computation
  - digitizing at POM minimizes EMI introduction
  - digital bus requires less cabling then analog





Pattern Recognition Results

PREDICTED	No Damage		Drilled Hole				Delamination				Impact			
ACTUAL		ND	1/32"	1/8"	¼"	½"	¼"	½"	1"	1.5"	4"	8"	16"	32"
No Damage	ND	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Drilled Hole	1/32"	0%	**86%**	14%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	1/8"	0%	53%	**47%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	¼"	0%	0%	0%	**44%**	56%	0%	0%	0%	0%	0%	0%	0%	0%
	½"	0%	0%	0%	0%	**100%**	0%	0%	0%	0%	0%	0%	0%	0%
Delamination	¼"	0%	0%	0%	0%	0%	**99%**	1%	0%	0%	0%	0%	0%	0%
	½"	0%	0%	0%	0%	0%	58%	**30%**	12%	0%	0%	0%	0%	0%
	1"	0%	0%	0%	0%	0%	1%	9%	**58%**	32%	0%	0%	0%	0%
	1.5"	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	0%
Impact	4"	0%	0%	0%	0%	0%	0%	0%	0%	0%	**76%**	23%	1%	0%
	8"	0%	0%	0%	0%	0%	0%	0%	0%	0%	6%	**33%**	61%	0%
	16"	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	**98%**	0%
	32"	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	14%	**86%**

- K-Nearest Neighbor (KNN) pattern recognition code employed
  - supervised learning algorithm
  - state based on majority category of optimized "K" nearest data sets
- Confusion matrix shows statistical accuracy of KNN predictions

Pattern Recognition Discussion

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- Results of PR-based methodology have been very successful
  - obtained using an optimized K-Nearest Neighbor code
  - **100%** presence accuracy without any false positives or missed damage
  - **100%** type of damage accuracy without any mis-classifications
  - **99.9%** severity prediction including adjacent levels (77% without)
- Sufficient results for technician to make a repair decision
  - achieve “adjacent” results by intelligently selecting severity boundaries
  - accuracy would improve with additional training data
- Achieved using separate plates for training and testing
  - broad implications for feasibility of eventual commercial implementation
  - single validated training data set needs to be deployed for entire fleet
  - can account for variability in sensor fabrication and placement
  - accommodate “real” damage types such as delamination and impact

Adaptive Compensation for PR

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- Adaptation modules inserted at the signal and feature levels
  - transformation vectors for addition/subtraction, scaling and translating
  - operations performed in multiple domains (time, frequency, wavelet, etc)
- Adaptive testing executed similarly to standard test procedure
  - baseline from “known good state” used to accommodate perturbation
  - assumes that baseline is collected within a known no-damage condition
  - assumes difference between baselines are within tolerable threshold
- Methodology to compensate for small perturbations in signals
  - uses perturbed training input from simulated and/or experimental data
  - goal of minimizing impact on the algorithm accuracy
  - adaptation parameters are locked after training for adaptive testing
  - confidence levels for each state as a function of perturbation level

Adaptive Training Flowchart

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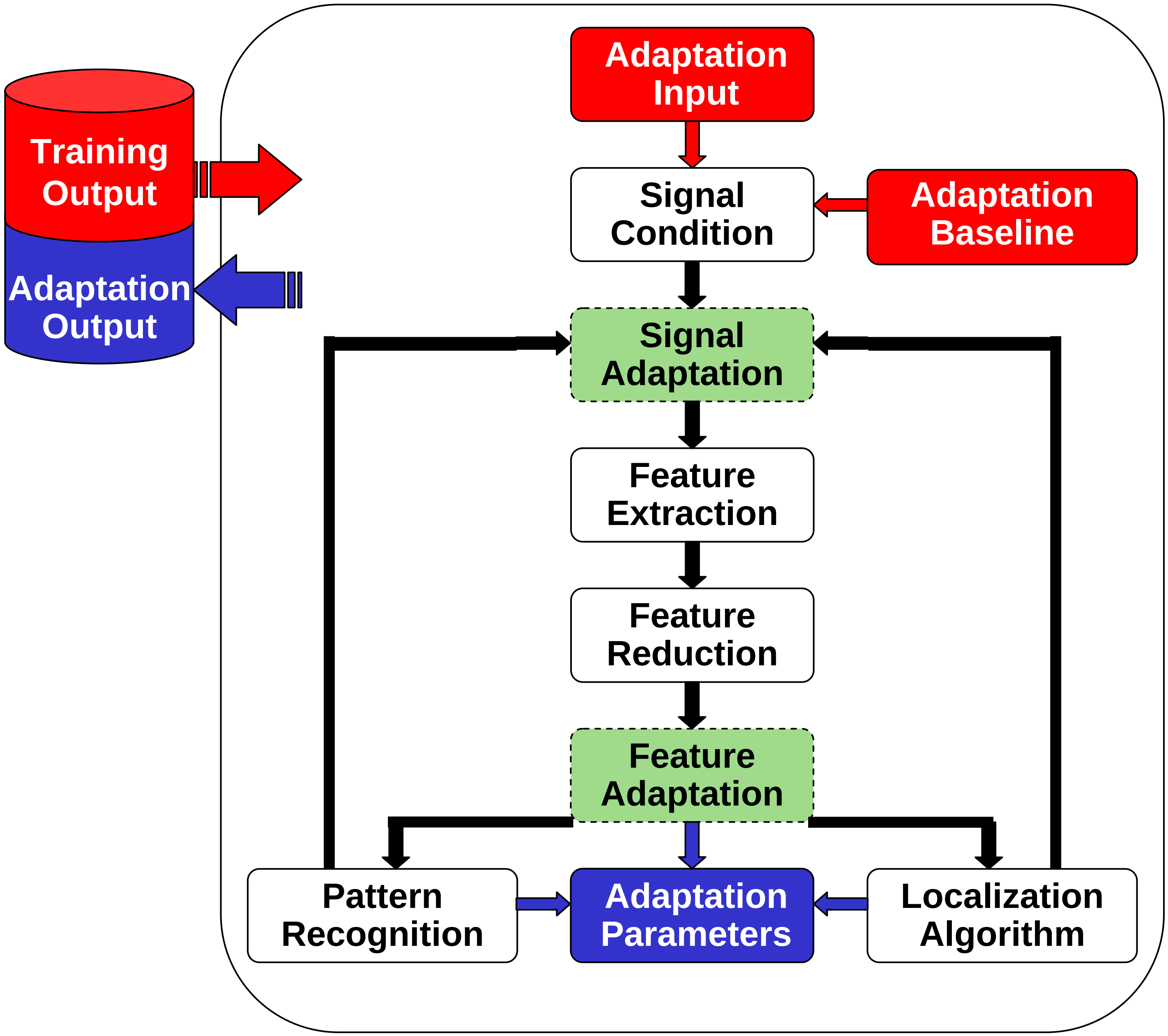
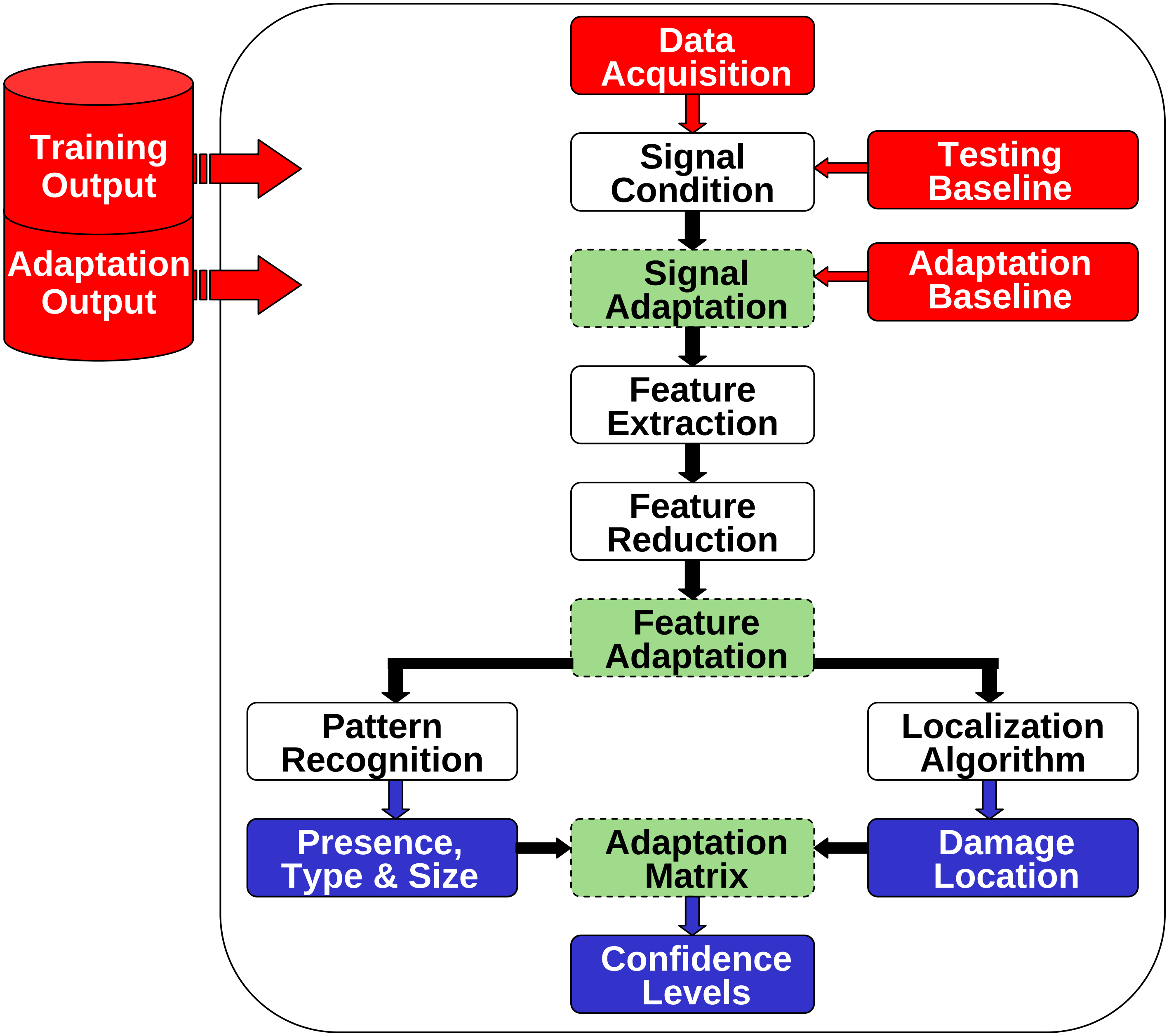


Adaptive Testing Flowchart



Simulated Implementation

- Application of this adaptive methodology is presented
  - goal to achieve first-order feasibility validation
  - uses the experimental data collected previously for PR study
  - simulated perturbations were introduced into baseline and test signals
  - subsequently Adaptive Training and Testing flowcharts were executed
- Three types of perturbations simulated separately
  - time delay between 0-100μs
  - uniform amplitude attenuation between 0-10%
  - central frequency shift between 0-10%
- Compared with no adaptation (note that previous PR results had included adaptation for sensor variability, excluded here)

Time Domain Perturbation

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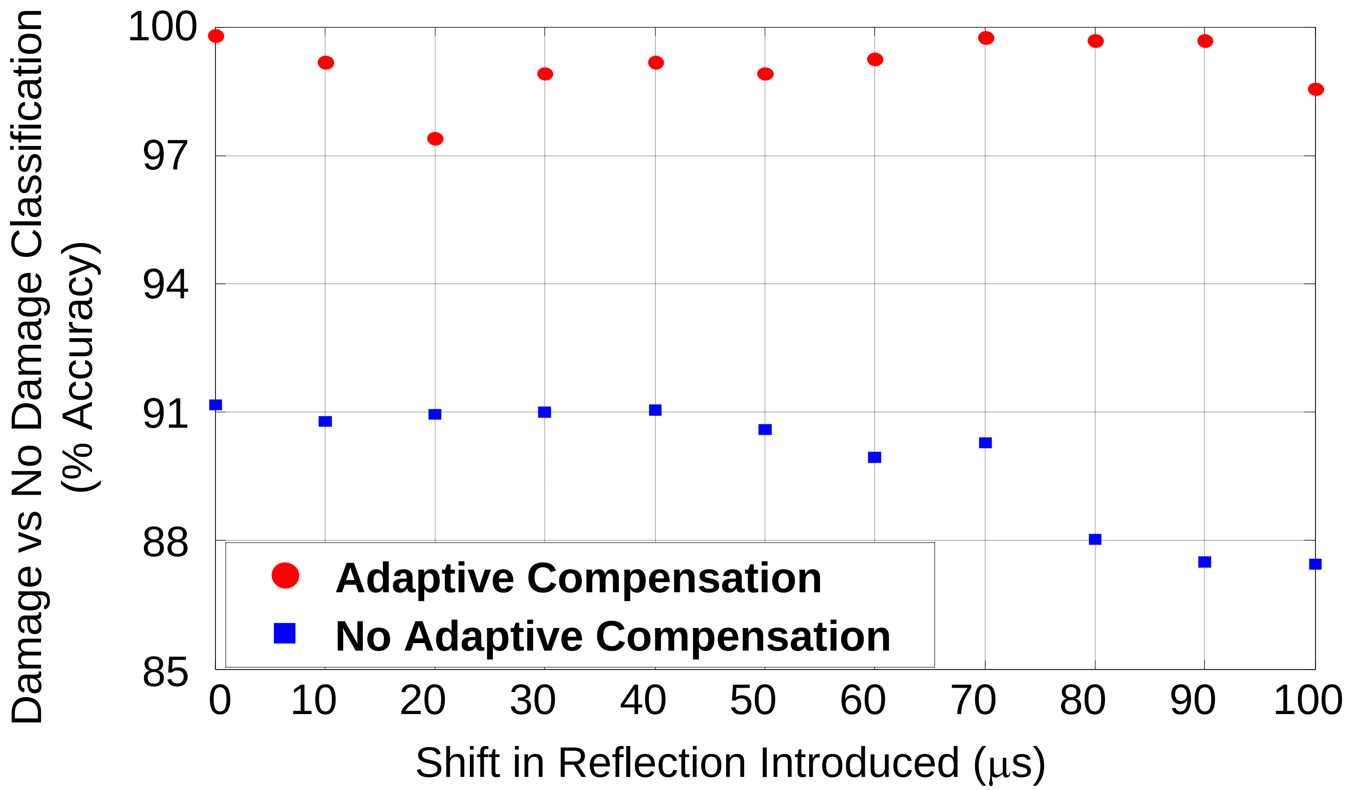
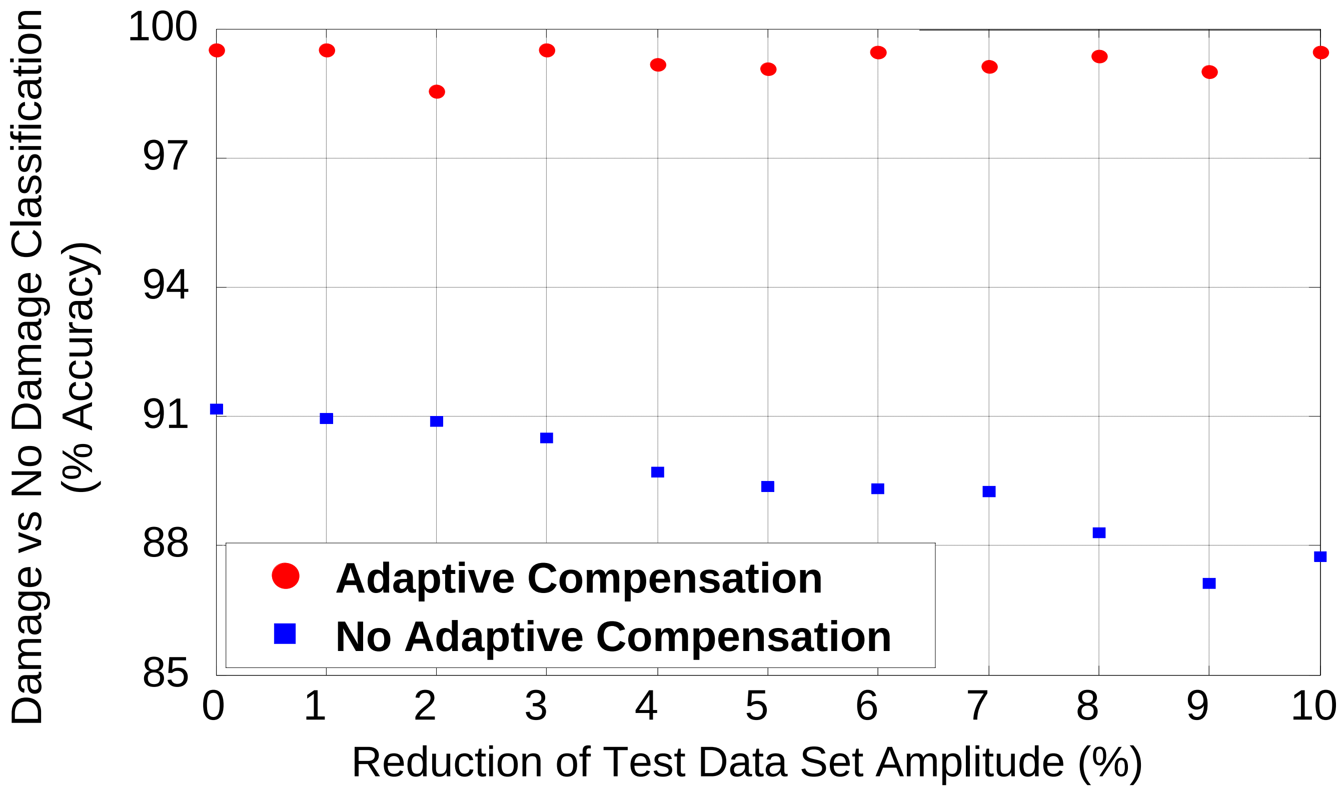


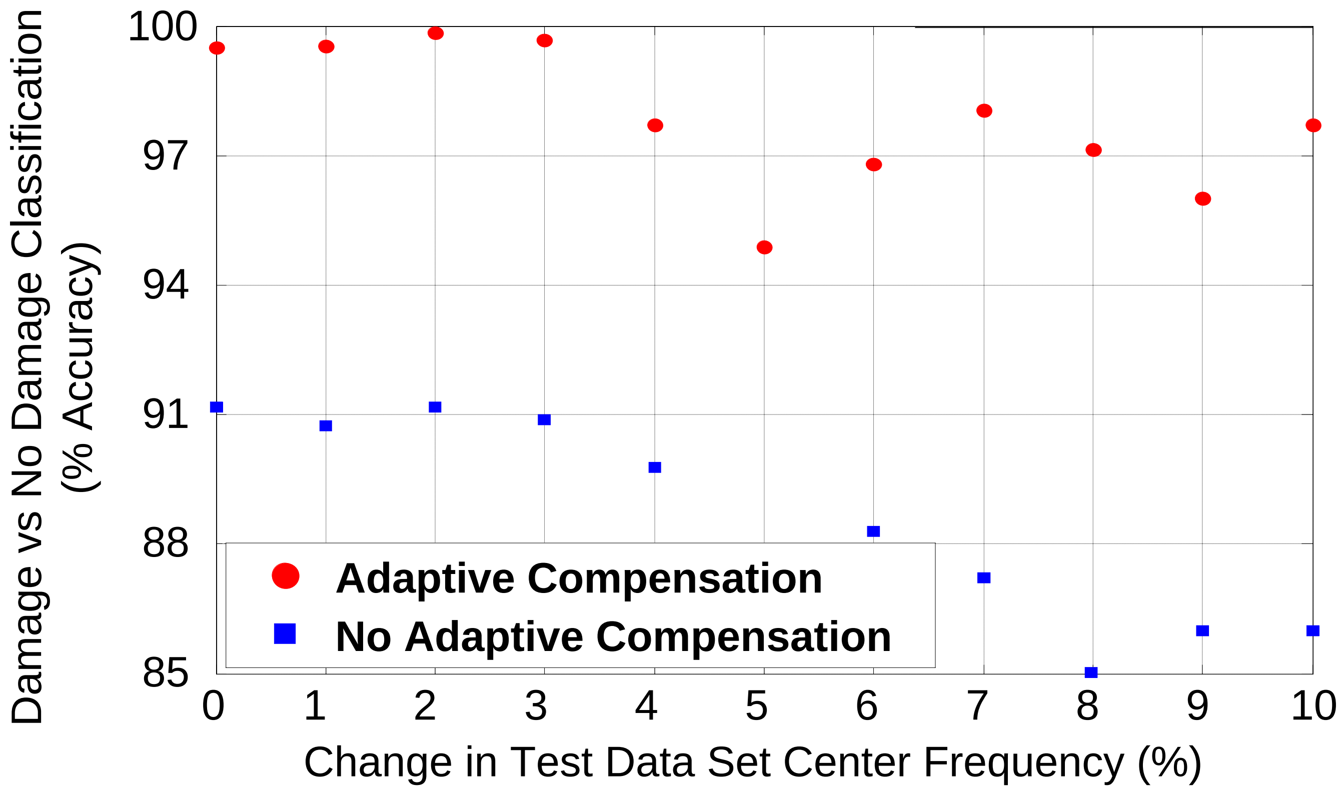
- Time delay between 0-100μs was introduced
- Represents change from repair moving a boundary condition
- Adaptation methodology is able to maintain >97% accuracy
- Traditional PR methodology accuracy degrades to <87%

Energy Domain Perturbation



- Uniform amplitude attenuation between 0-10% was introduced
- Replicates a degraded sensor bondline
- Adaptation methodology is able to maintain >98% accuracy
- Traditional PR methodology accuracy degrades to <87%

Frequency Domain Perturbation



- Central frequency shift between 0-10% was introduced
- Seen in ageing from microcracks reducing material modulus
- Adaptation methodology is able to maintain >95% accuracy
- Traditional PR methodology accuracy degrades to <85%

Conclusions

- Adaptive compensation SHM methodology presented
  - accommodates perturbations caused by ageing, maintenance & repairs
  - designed to maintain/account for damage detection algorithm accuracy
  - flowcharts given for training algorithm and adaptation modules, testing
  - adaptation modules are inserted at both the signal and feature level
  - transforms based upon differences between original and new baseline
- Damage detection results presented with simulated ageing
  - perturbations up to 10% in signal time, energy and frequency domains
  - standard algorithm exhibits decreasing accuracy with more variability
  - adaptive algorithm maintains accuracy by incorporating new baselines
- Successfully demonstrates feasibility of adaptive modules to compensate for signal perturbations not attributable to damage
  - work remains to fully develop methodology for commercial applications
  - extend investigation to damage type, severity and location
  - experimental validation beyond pure simulation
  - using analytical and/or finite element models to train for perturbations

Acknowledgments

- The initial pattern recognition portion of this research was sponsored by the Air Force Research Laboratory Materials and Manufacturing Directorate (AFRL/ML)
  - SBIR Phase I award FA8650-06-M-5026
  - “Damage Identification Algorithms for Composite Structures”

- AFRL program managers:
  - Dr. Richard Hall
  - 2ndLt William Bridges