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# **An Adaptive Pattern Recognition Methodology for**

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# **Damage Classification in Composite Laminates**

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# Introduction

- Structural Health Monitoring (SHM) denotes a system with the ability to detect and interpret adverse “changes” in a structure in order to **reduce life-cycle** costs and **improve reliability**
- Essentially involves integrating non-destructive evaluation (NDE) devices into a vehicle to collect prognostic data
  - **SHM could reduce inspection/maintenance costs by 33% through CBM**
  - **can catch damage that may have occurred between scheduled intervals**
  - integrate SHM systems into new vehicles or retrofit for ageing vehicles
- Applicable to any field – highest payoff in air/spacecraft



# Problem Statement



- **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

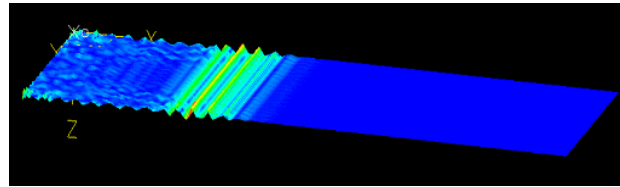


- Several challenges involved in detecting damage in composites
  - delamination and impact (below visible surface) dominate
  - modes may not be discrete (can interact)
- Ideally top-level binary categorization of pristine or damaged
  - taking micromechanics view materials inherently have flaws
  - microscopic flaws grow slowly, accelerated overload or impacts events
  - **damage threshold must be defined for some detectable flaw size level**
- Would like further classification beyond presence of damage
  - 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

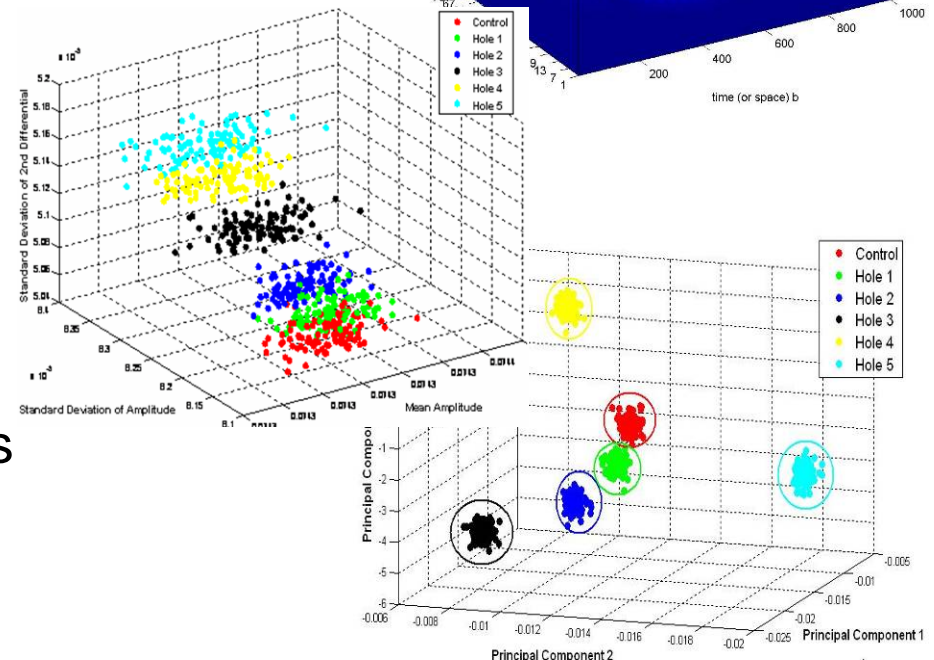
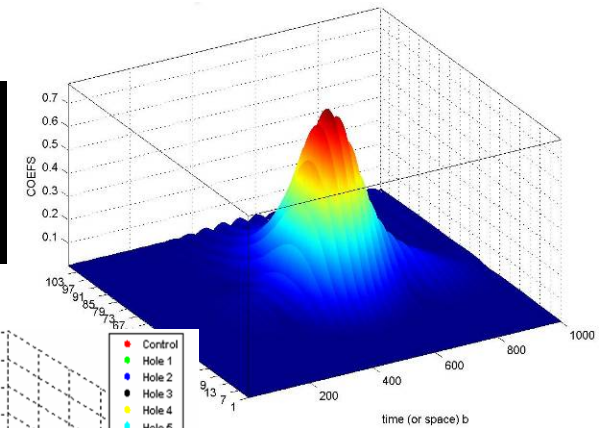
- discriminative features for analysis
- time, frequency & energy domains

- Feature Selection

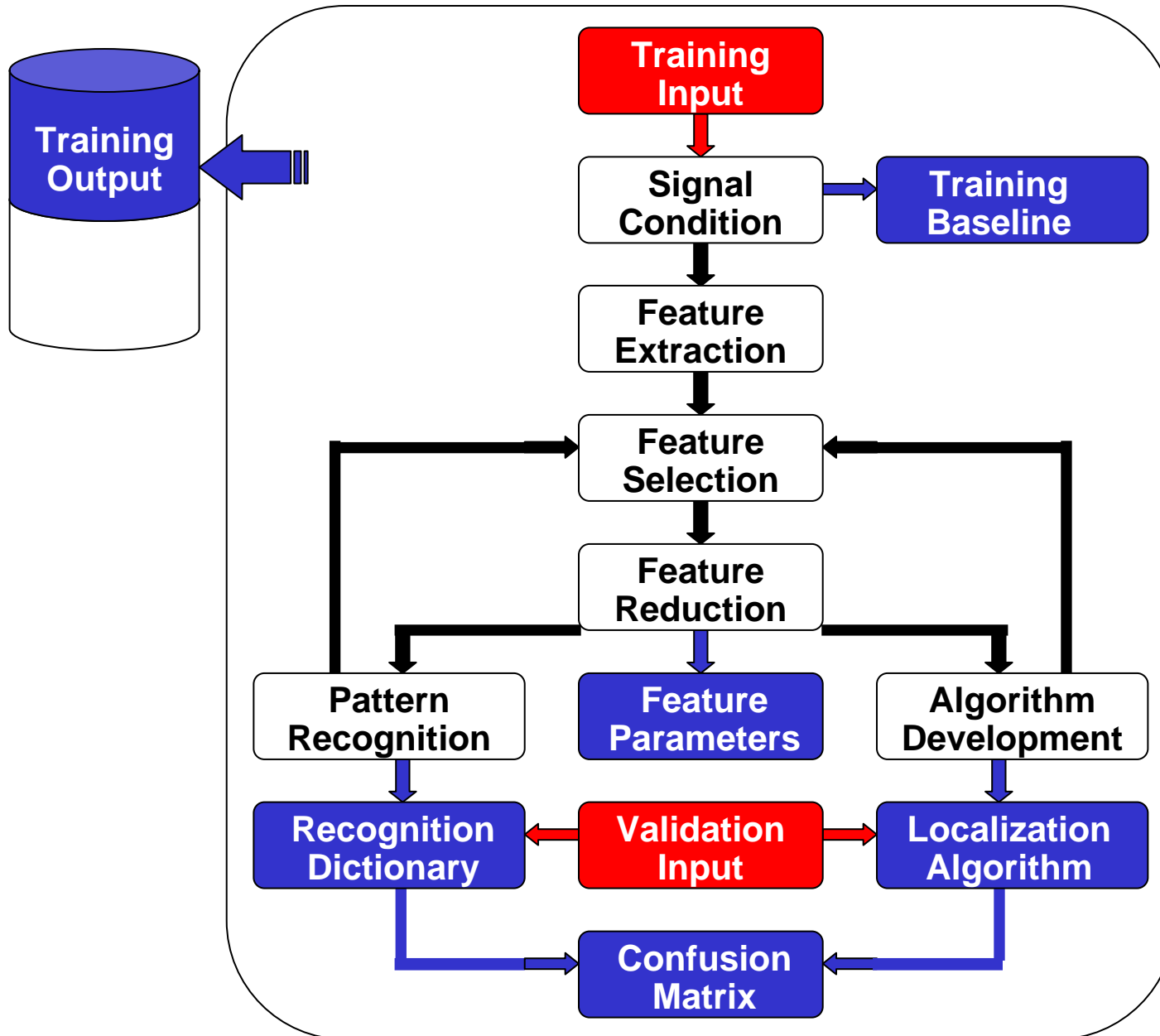
- repeatable features unique to class
- can reduce dimensionality (PCA)

- Algorithms

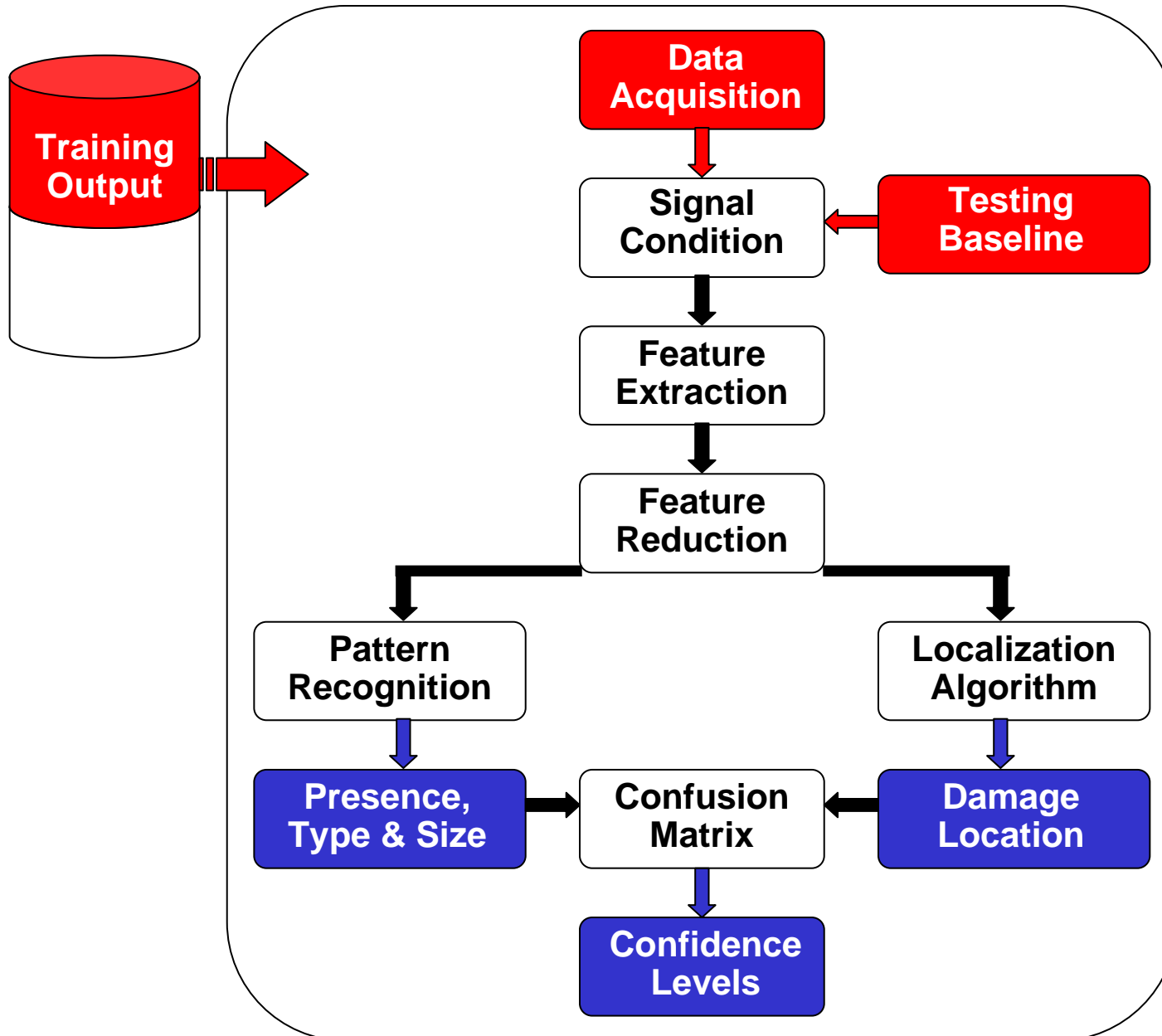
- Pattern Recognition (PR) to identify damage presence, type and severity
- localization performed with convention single or multi-sensor methods
- confusion matrix can be used to calculate confidence levels



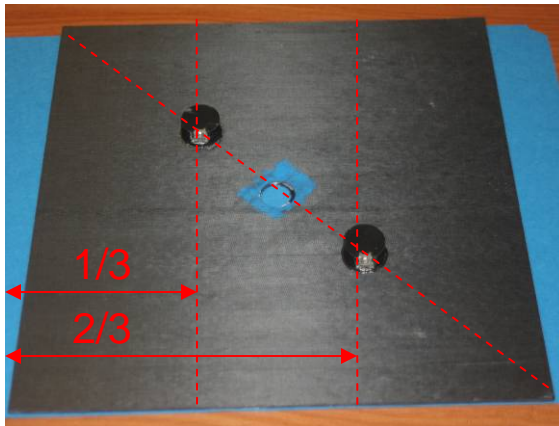
# Standard Training Flowchart



# 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", 1/4", 1/2"
3	Delamination (corner cut)	1/4", 1/2", 1", 1.5"

- 11.75" x 0.1" square quasi-isotropic CFRP laminates, 2 nodes
- Lamb wave tests at 100kHz using M.E.T.I.-Disk 3 SHM nodes
- 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

# Pattern Recognition Results

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

- **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



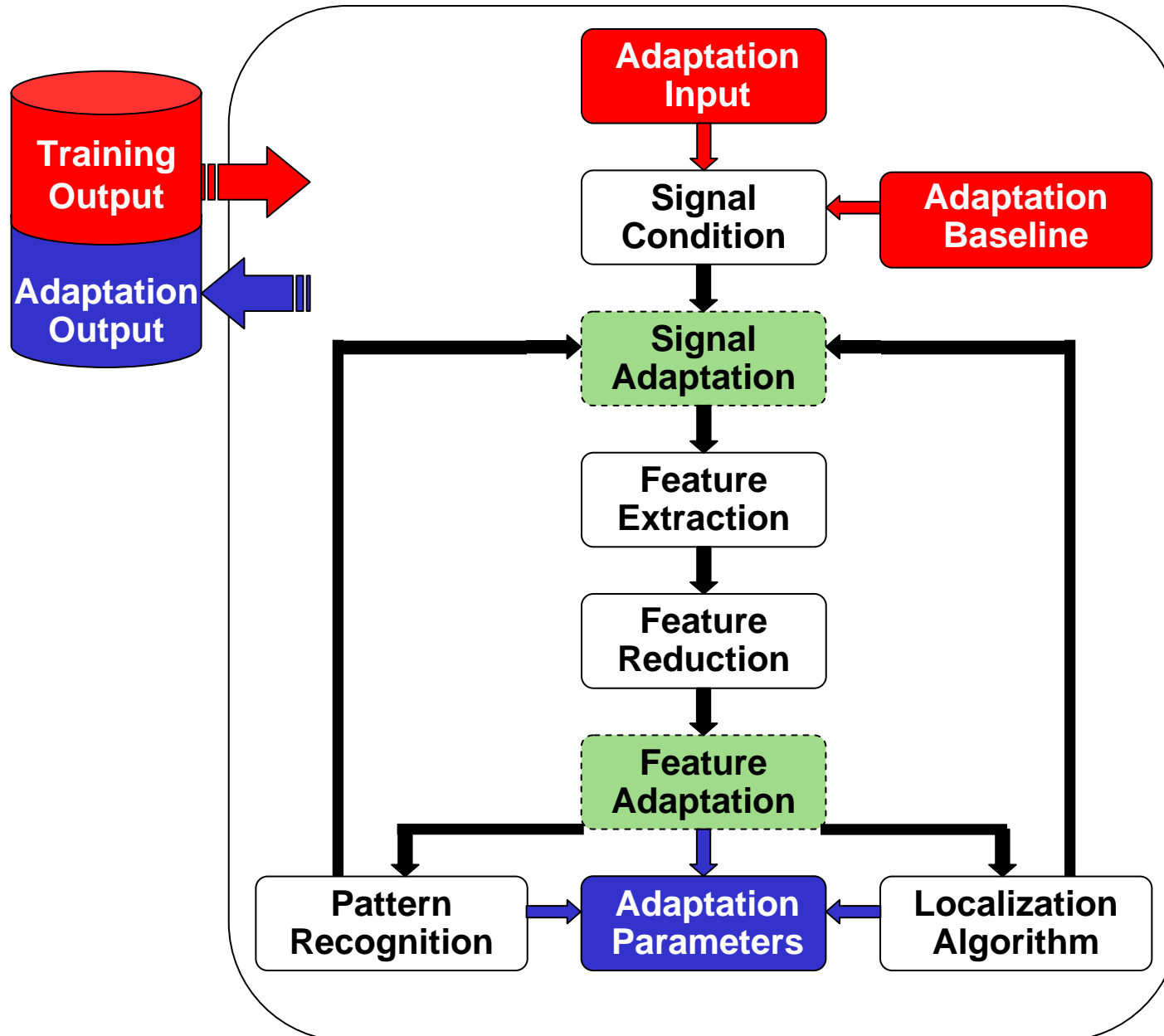
- Results of PR-based methodology have been very successful
  - obtained using an optimized K-Nearest Neighbor code
  - **100%** presence accuracy without any false positives or missed damage
  - **100%** type of damage accuracy without any mis-classifications
  - **99.9%** severity prediction including 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

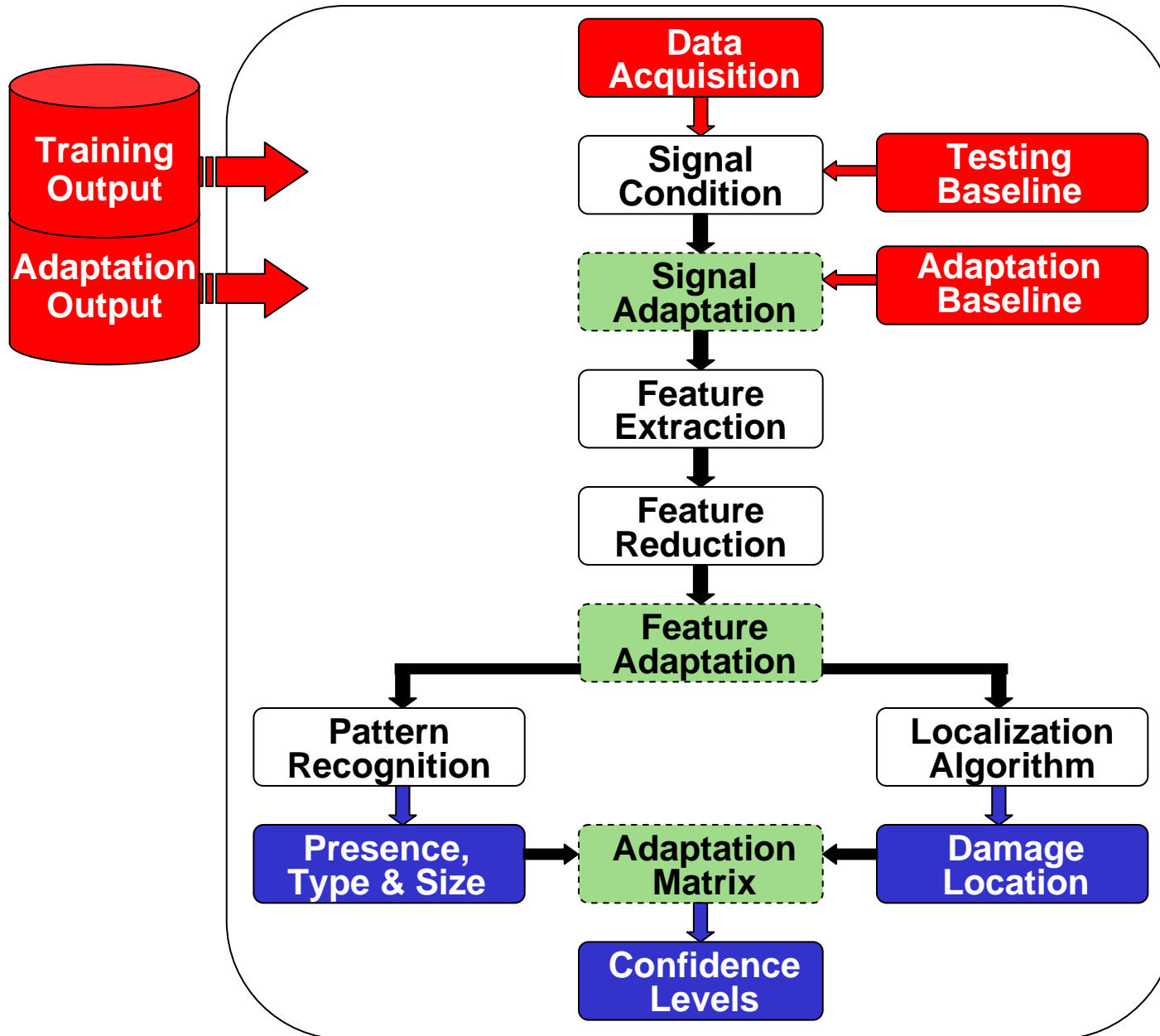


- Adaptation modules inserted at the signal and feature levels
  - transformation vectors for addition/subtraction, scaling and translating
  - operations performed in multiple domains (time, frequency, wavelet, etc)
- Adaptive testing executed similarly to standard test procedure
  - baseline from “known 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**
  - confidence levels for each state as a function of perturbation level
  - simulated perturbations were introduced into baseline and test signals

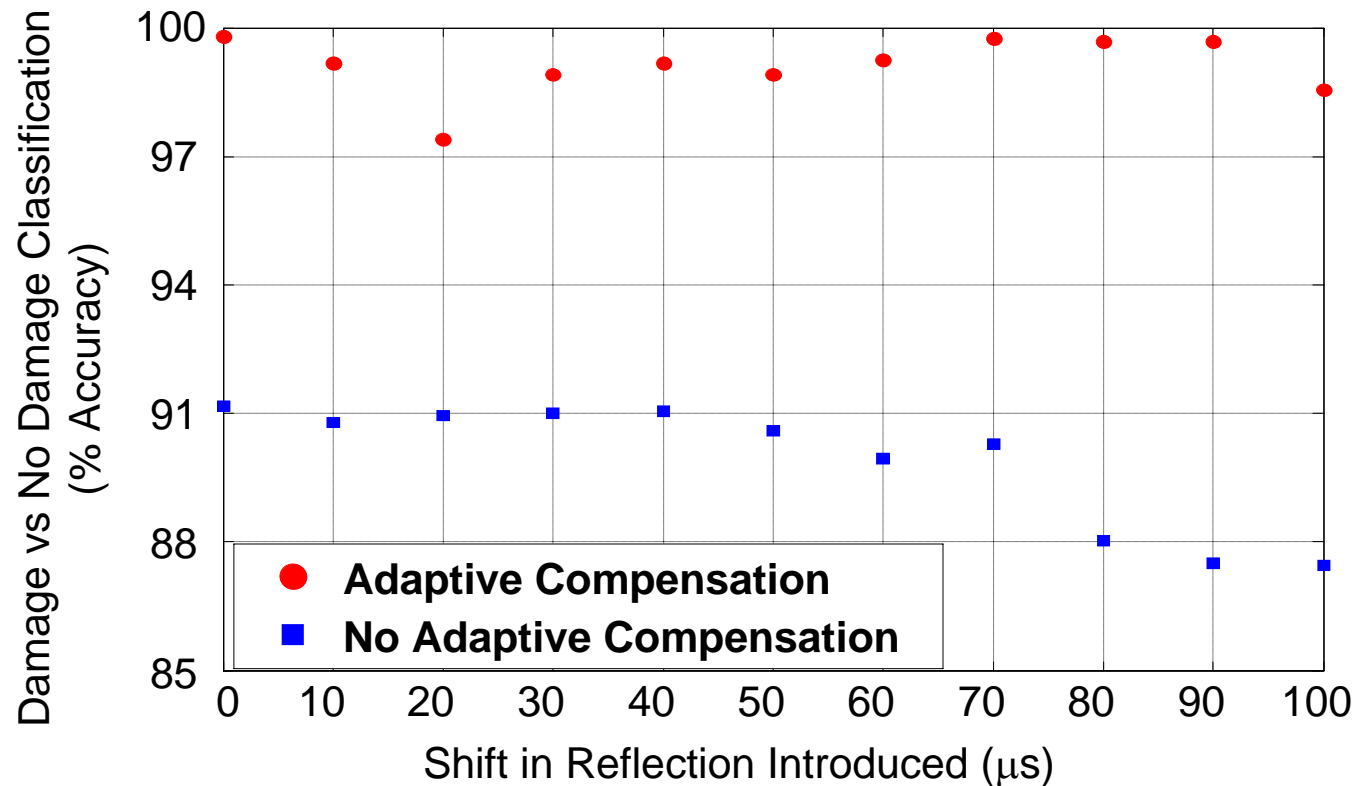
# Adaptive Training Flowchart



# Adaptive Testing Flowchart

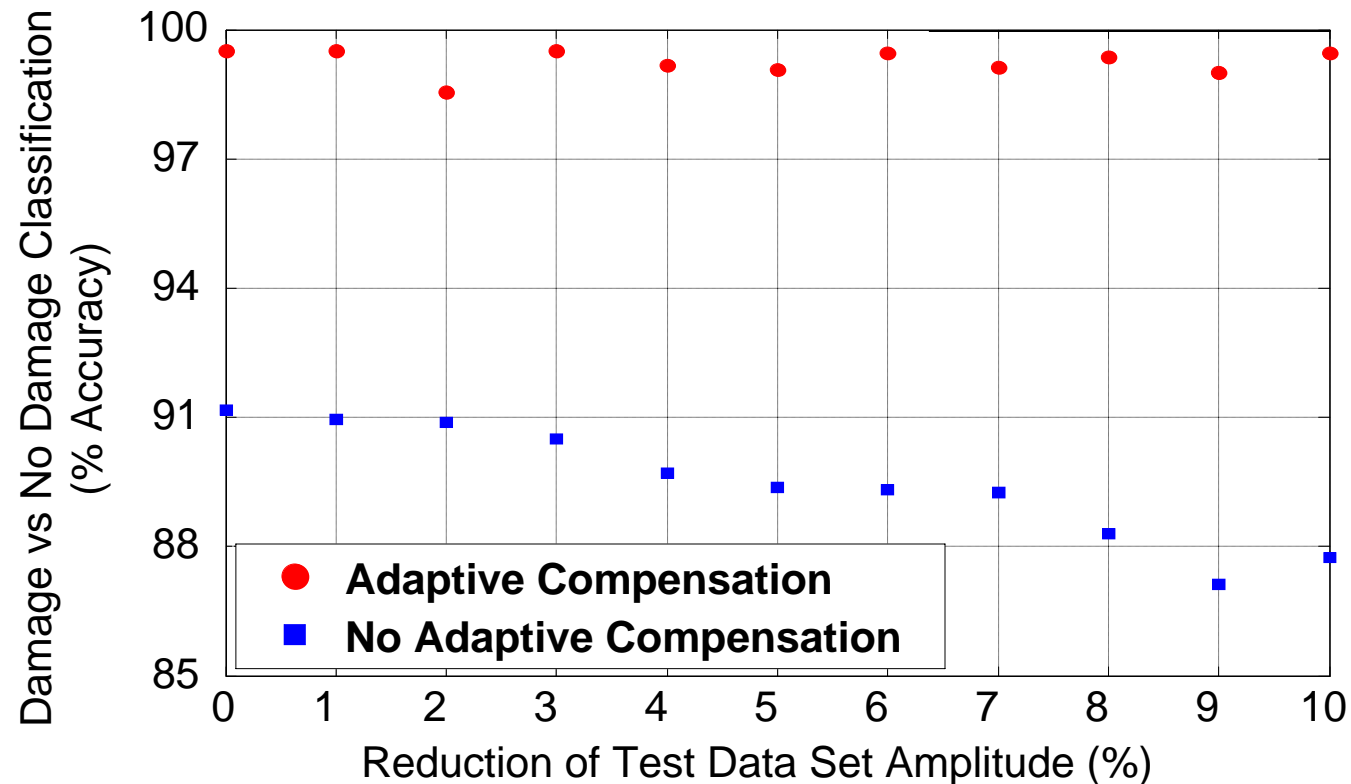


# Time Domain Perturbation



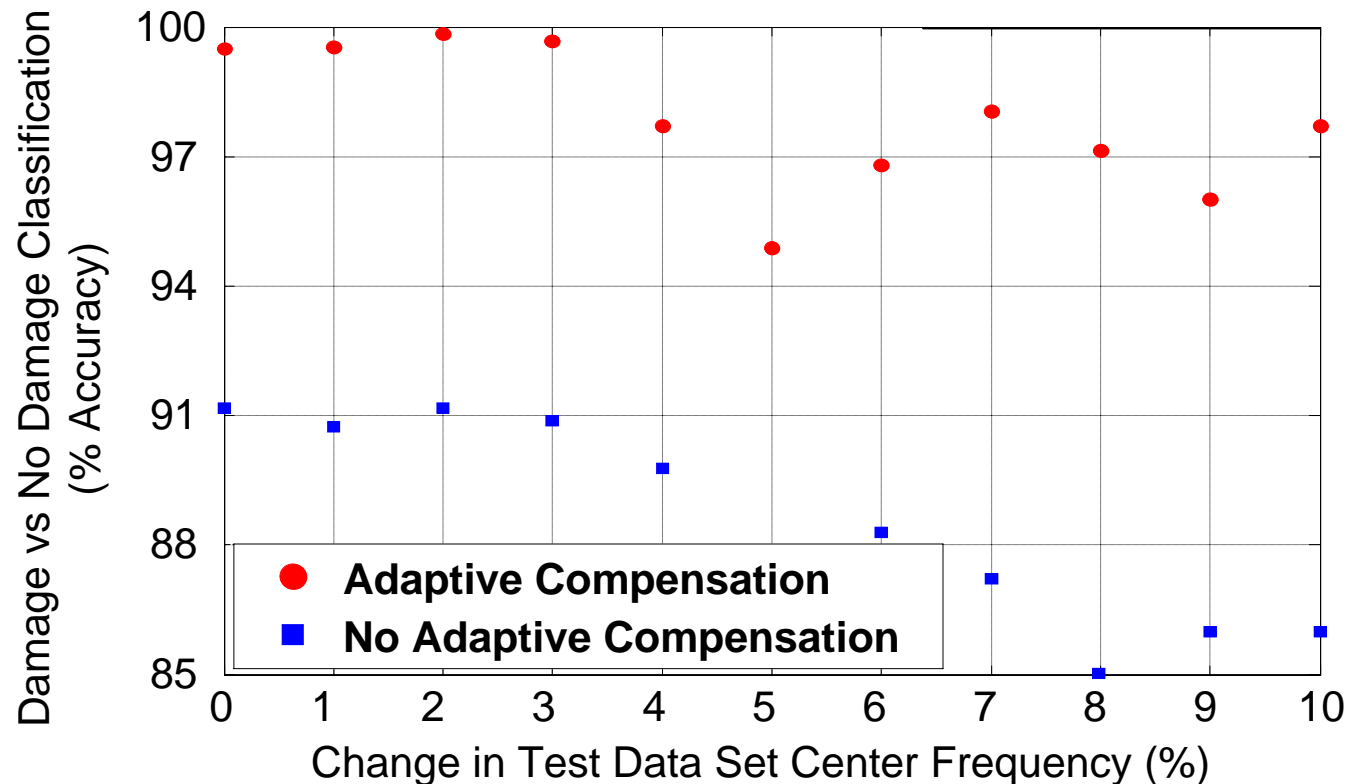
- Time delay between 0-100 $\mu\text{s}$  was introduced
- Represents change from repair moving a boundary condition
- **Adaptation methodology is able to maintain >97% accuracy**
- **Traditional PR methodology accuracy degrades to <87%**

# 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

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