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Pattern Recognition for Damage Characterization in Composite Materials

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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 reduces 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

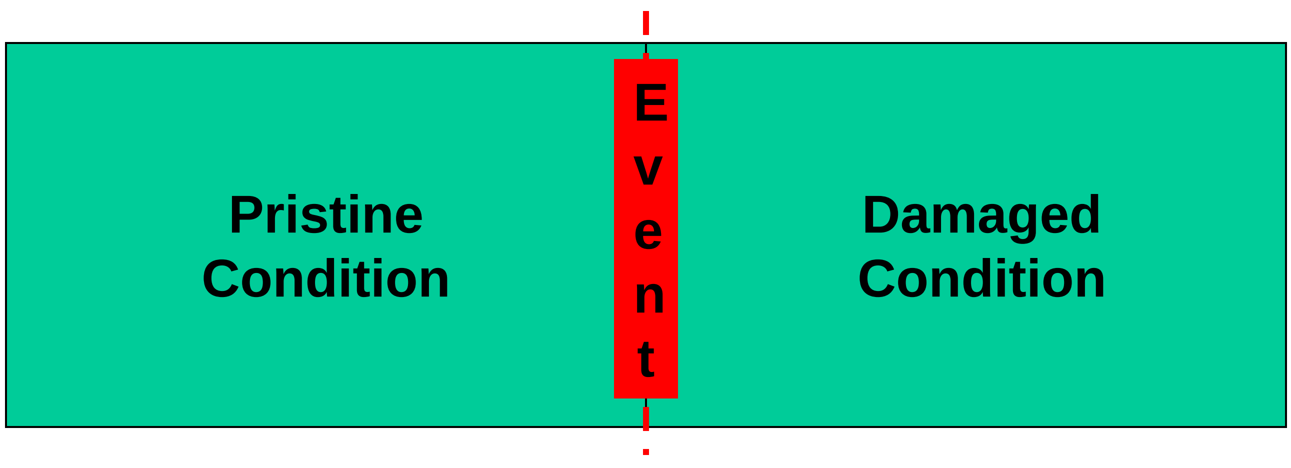




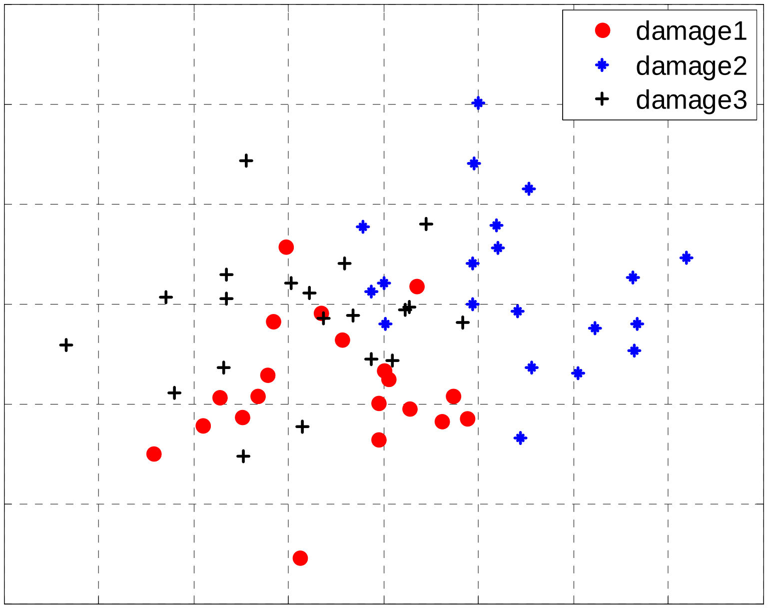

Damage in Composite Materials

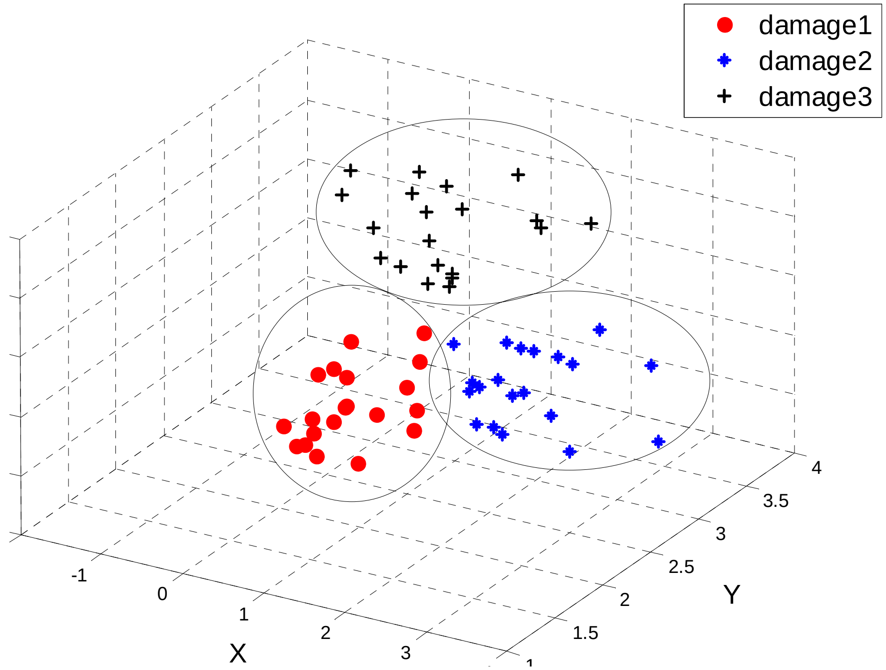
- Several challenges involved in detecting damage in composites
  - metals: corrosion and fatigue vs. composites: delamination and impact
  - modes interact, conducting fibers within insulative matrix
  - damage often below the visible surface, visual inspection overlooks

- Categorization of damage in composites
  - ideally would like a binary top-level pristine or damaged categorization
  - taking micromechanics view, material is fabricated with flaws
  - microscopic flaws grow slowly, accelerated overload or impacts events
  - damage threshold must be defined for some detectable flaw size level



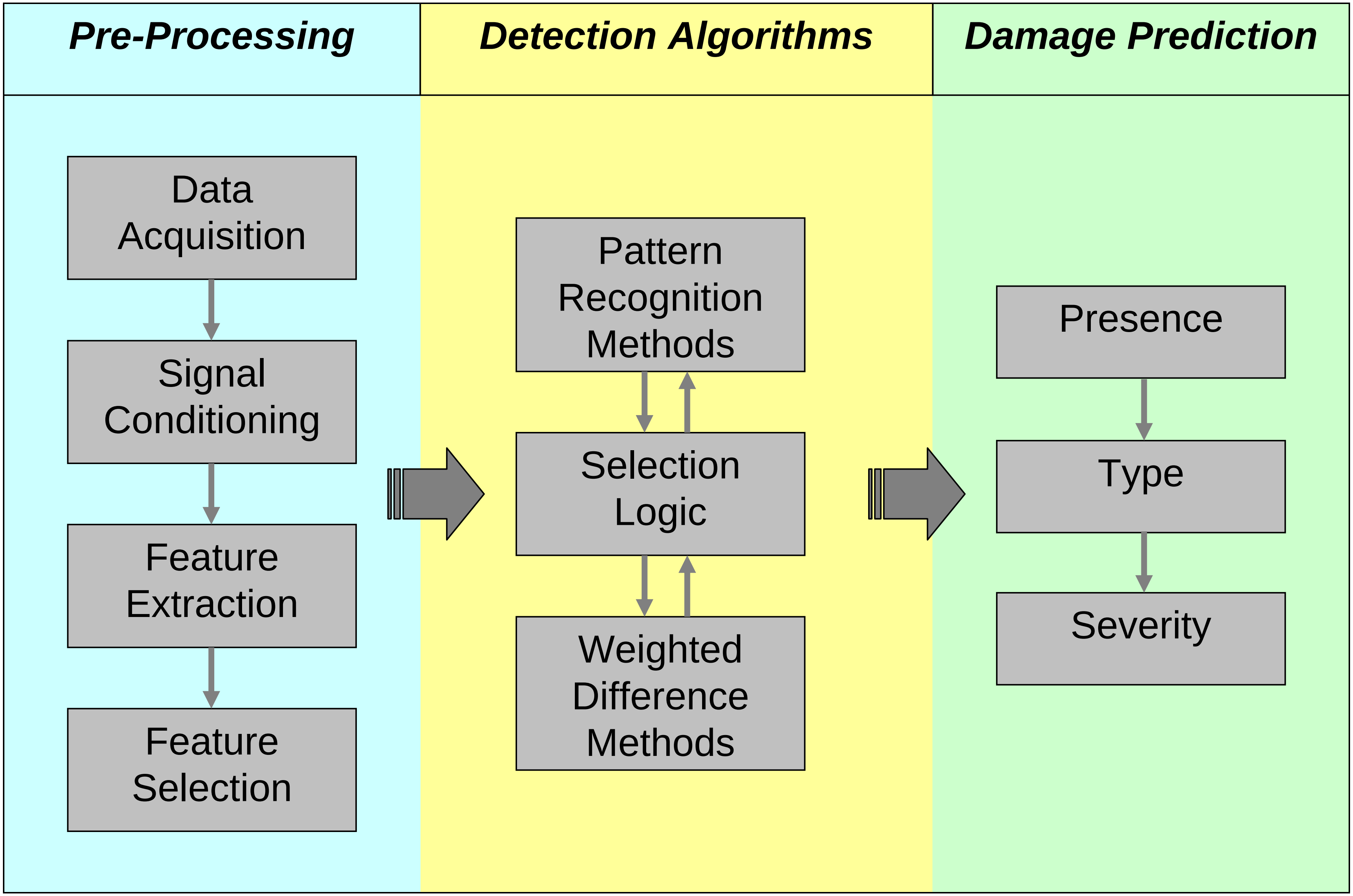
State Classification





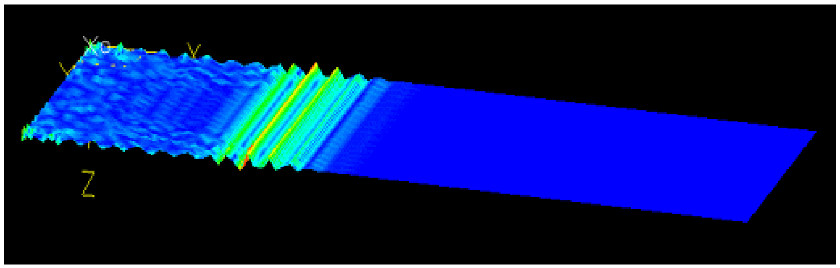
- Would like further classification beyond presence of damage
  - limited features may be used to separate damage and no damage
  - potential for large mode space for composites
  - may not be feasible to distinguish between modes if linearly inseparable
- Must extract many separate features for detailed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

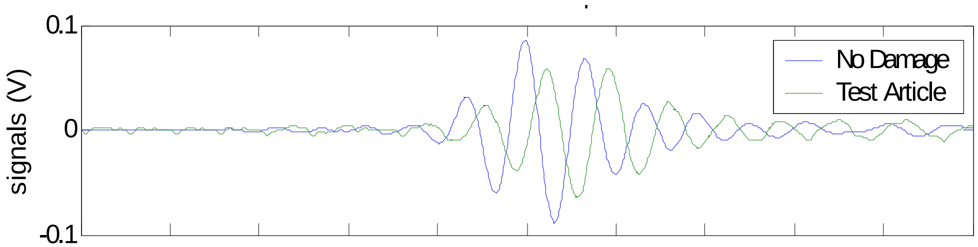
Methodology



Data Acquisition

- Lamb wave is an elastic perturbation propagating in solid media
  - excitation shape and frequency can be optimized for particular geometry
  - group velocity approximately ∝ (E/ρ)1/2, damage slows down waves
  - reflected wave from damage can be used to determine locations
  - utilize concentric piezoelectric actuator/sensor pairs in pulse-echo mode
- Many advantages to Lamb waves over traditional methods
  - best damage size and range to sensor size ratios
  - sensitivity and range scales with input power level (with limitations)





Signal Conditioning

- Employed to de-noise acquired signal from unwanted content
- Noise can generally be described by 2 categories
  - incoherent or “white” noise can be removed through averaging
  - coherent or EMI noise can be extracted in the frequency domain
  - close attention must be paid to signal phase
- Another important component is removal of unwanted artifacts
  - could include boundary conditions as well as pre-existing conditions
  - achieved by various methods in time, frequency and/or wavelet domains
  - eliminate misleading signal characteristics, typically by using baselines

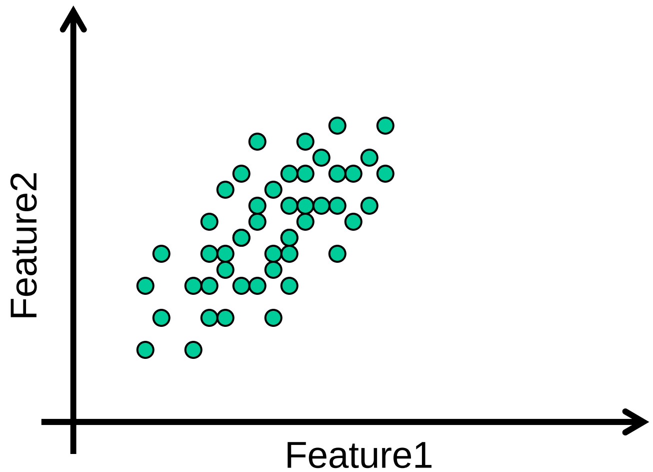
Feature Extraction

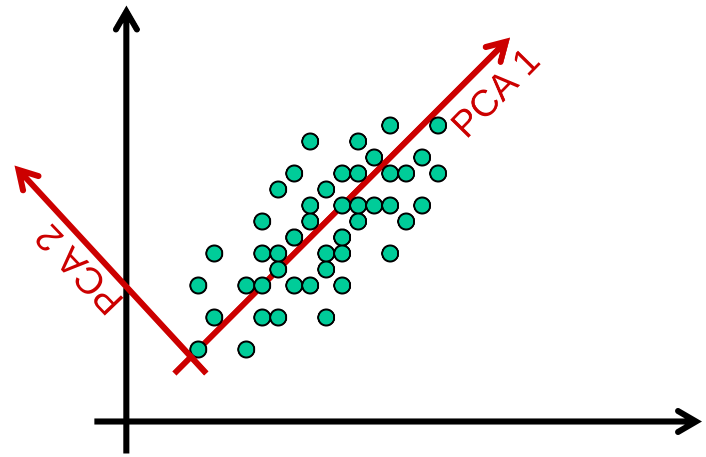
- Discriminative features from Lamb waves needed for analysis
- Time Domain features
  - time of flight, time position of max and subsequent secondary peaks
  - time features can be observed from raw data itself with little processing
- Frequency Domain features
  - max PSD value, shift in frequency response from baseline, phase value
  - frequency features extracted using Fourier or Wavelet decomposition
- Energy Domain features
  - max amplitude, total energy, mean/dev for signal,1st and 2nd difference
  - features extracted through time and frequency-based functions

Feature Selection

- Select most representative and discriminative features from set
  - too few features could result in reduced accuracy
  - larger set does not imply better classification, may degrade performance
- Many ways to select producing varying accuracy and efficiency
- Traditional method is one-way Analysis of Variances (ANOVA)
  - accomplished by comparing means of columns of data
  - selection based on probability that feature is unique to particular states
- Principal Component Analysis (PCA)
  - technique for reducing dimensionality of dataset
  - transform multi-dimensional coordinate system to maximize variability

Feature Selection - PCA





- Natural coordinate system of data is transformed
  - original data represented as voltage vs time or intensity vs frequency
  - greatest variance captured by the 1st coordinate (1st principal component)
  - 2nd greatest variance by the 2nd coordinate, etc
- Select principal components that encapsulate most variability
  - data can be reconstructed with low order dimensionality
  - remaining components can be discarded
  - 20 PC's capture 70% of the variability for 1000 point voltage vs time data

Weighted Difference Algorithms

Undamaged plate

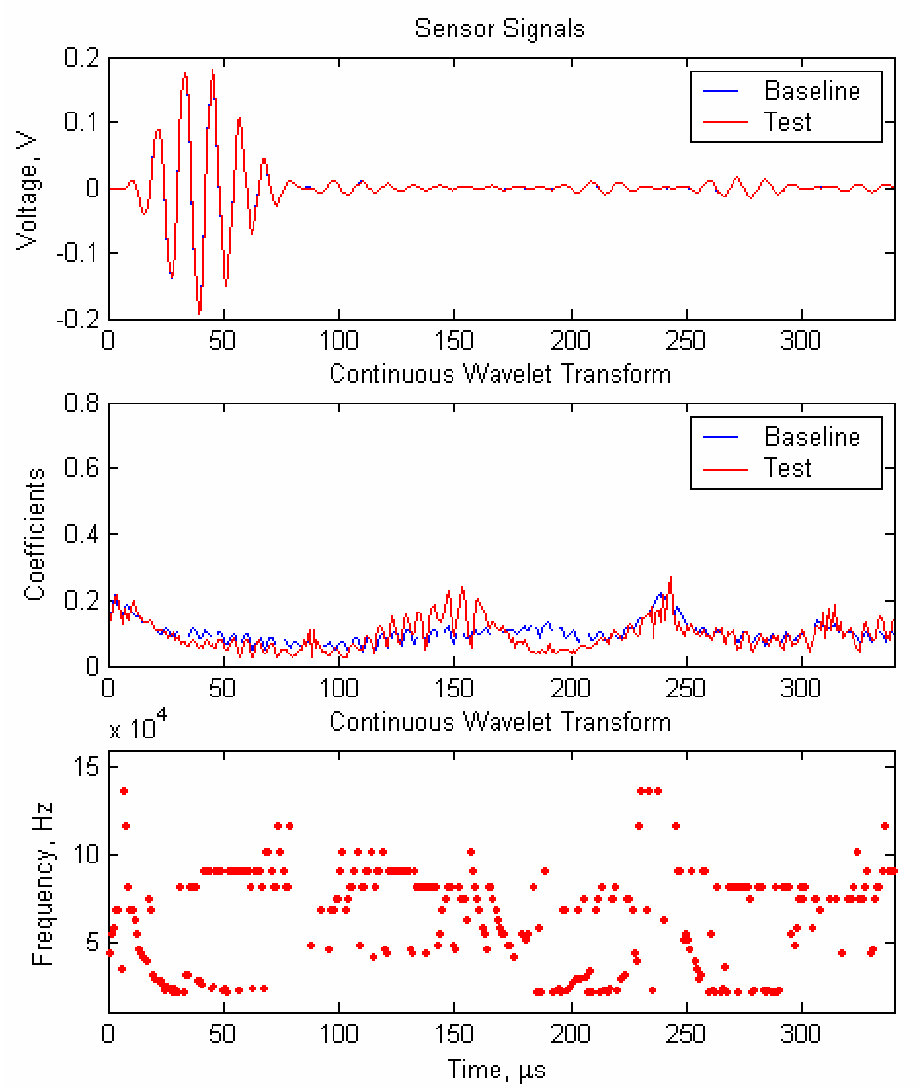
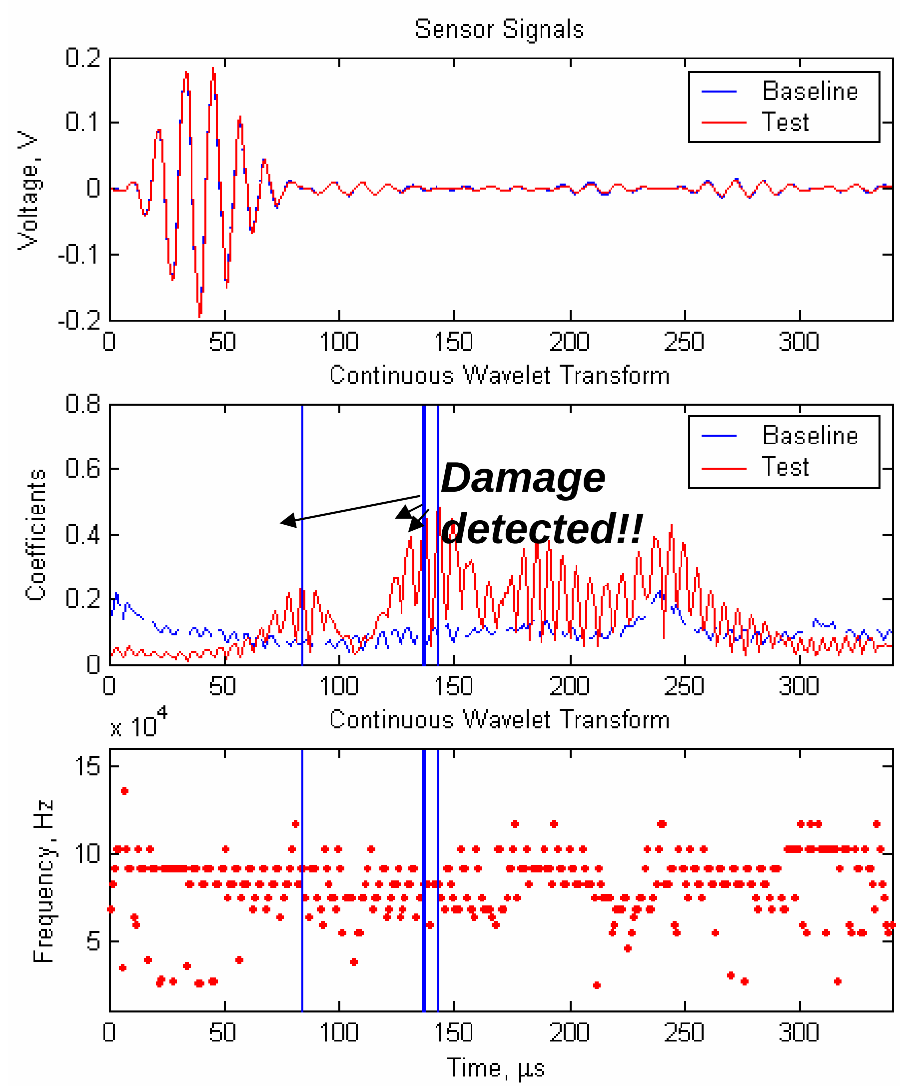


Plate with simulated damage



Pattern Recognition Algorithms

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- Collection of mathematical models used to associate a set of test data with one of several pre-designated classifications
  - some methods are statistical, others have learning capabilities
  - all PR methods require training sets to define class “profile”
- 3 different pattern recognition techniques were investigated
  - *K-Nearest Neighbor (KNN)*
  - *Neural Network*
  - *Decision Tree*
- Each method was implemented independently, as well as in combination with other methods bound by simple logic

Pattern Recognition: Nearest Neighbor

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- Method
  - supervised learning algorithm
  - category of new data point is determined based on the closest neighbor
  - K-nearest neighbor is based on majority category of K-nearest neighbors
  - not a learning algorithm but based on memory where a new instance is based on input features and training samples
- Advantages
  - analytically tractable
  - simple implementation
  - uses local information, which can yield highly adaptive behavior
  - lends itself very easily to parallel implementations
- Disadvantages
  - large storage requirements (worse as K increases)
  - computationally intensive recall (worse as K increases)
  - most noise sensitive (particularly at low K values)

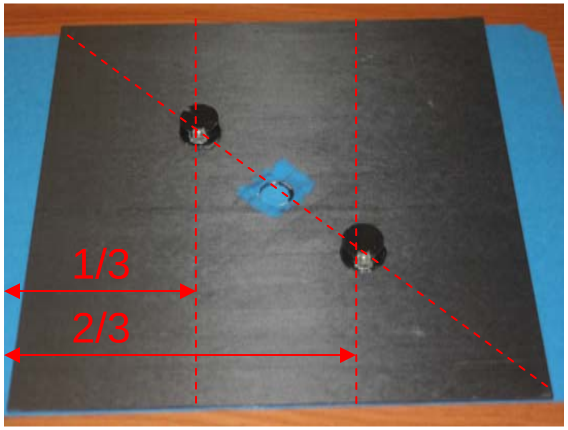
Pattern Recognition: Neural Networks

- Method
  - machine-learning technique that uses weighted links
  - simulates a network of communicating nerve cells
  - input/output data is utilized to train the network
  - network links are modified to capture the knowledge, so that after it has been adequately trained, it can be used to classify new input
- Advantages
  - applicable to multivariate non-linear problems & parallel implementation
  - no need to assume an underlying data distribution (statistical modeling)
  - robustness towards noisy data, well suited for sensorial data processing
- Disadvantages
  - minimizing overfitting requires a great deal of computational effort
  - model tends to be black box or input/output table without analytical basis
  - need for large training sets (exponentially more sets than defined states)

Pattern Recognition: Decision Tree

- Method
  - essentially a series of “questions and answers”
  - data enters “trunk” and “branches” represent conjunctions of features
  - lead to single classification or “leaf”
  - weight of each decision is implicit in the hierarchy of the branch structure
  - several trees assembled into “forest” can achieve a statistical consensus
- Advantages
  - requires the least data and accommodates missing features
  - in-built feature selection and weighing
  - tree structure inference builds domain knowledge
  - nonparametric or "distribution free"
- Disadvantages
  - unstable decision trees may be produced
  - data split only by one variable at a time, rules deduced may be complex
  - trees may be overfitted

Experimental Setup

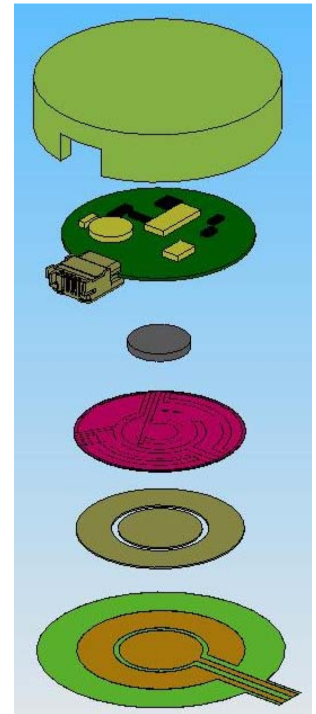


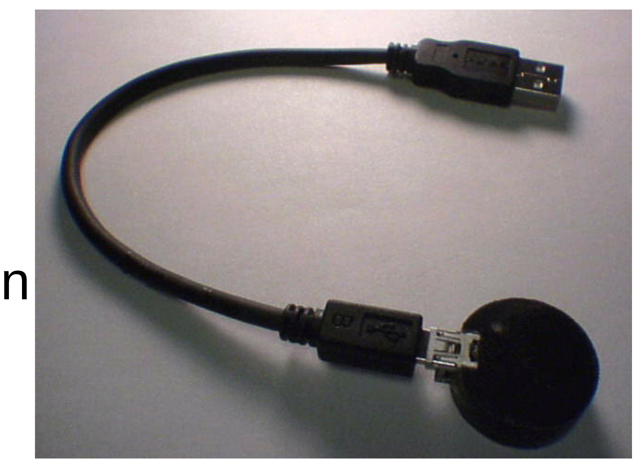
Plates	Damage Type	Damage Severity
3	Impact (5 lbs dropped weight)	4”, 8”, 16”, 32”
3	Hole (center drilled)	$^1/_{32}$”, $^1/_8$”, ¼”, ½”
3	Delamination (corner cut)	¼”, ½”, 1”, 1.5”

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

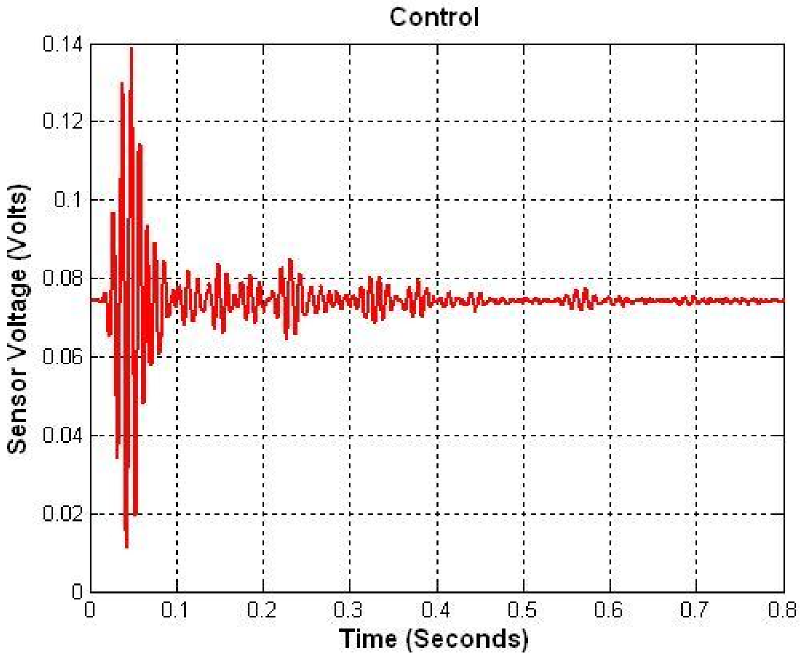
M.E.T.I.-Disk 3 Digital SHM Nodes

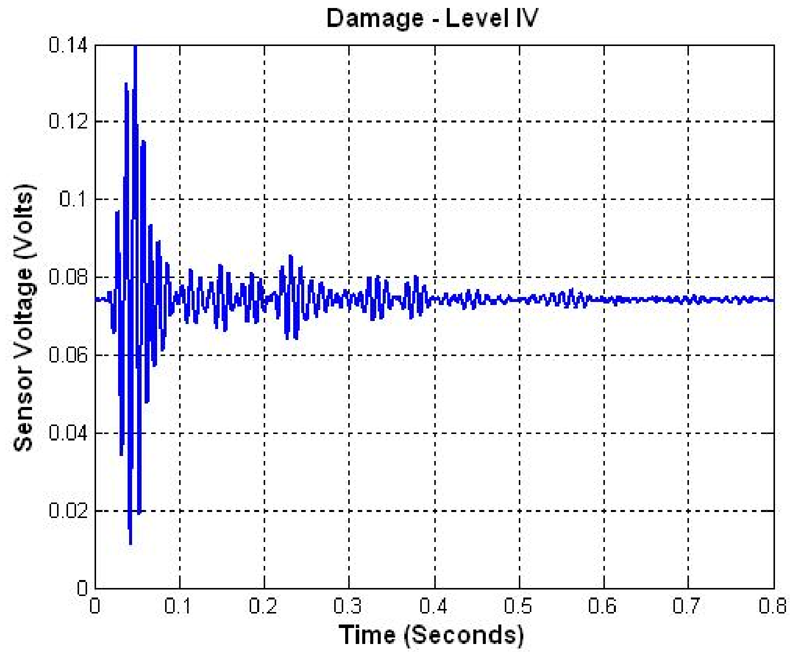
- Monitoring & Evaluation Technology Integration
  - concentric piezoceramic sensor/actuator elements
  - rigid-flex technology used for ADC & DAC
  - mini-USB connector for power and data transfer
  - 1” diameter urethane encapsulation for durability
- Digital SHM infrastructure (TRL 6 demonstrated)
  - 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





Experimental Results





- Representative raw voltage versus time for center-drilled hole
  - compares signals from the undamaged plate with most severe ½" hole
  - visually signals appear nearly identical in the time domain
- 16 total features were extracted from 3-domains
- Both ANOVA & PCA-based selection approaches investigated

Cluster Plots

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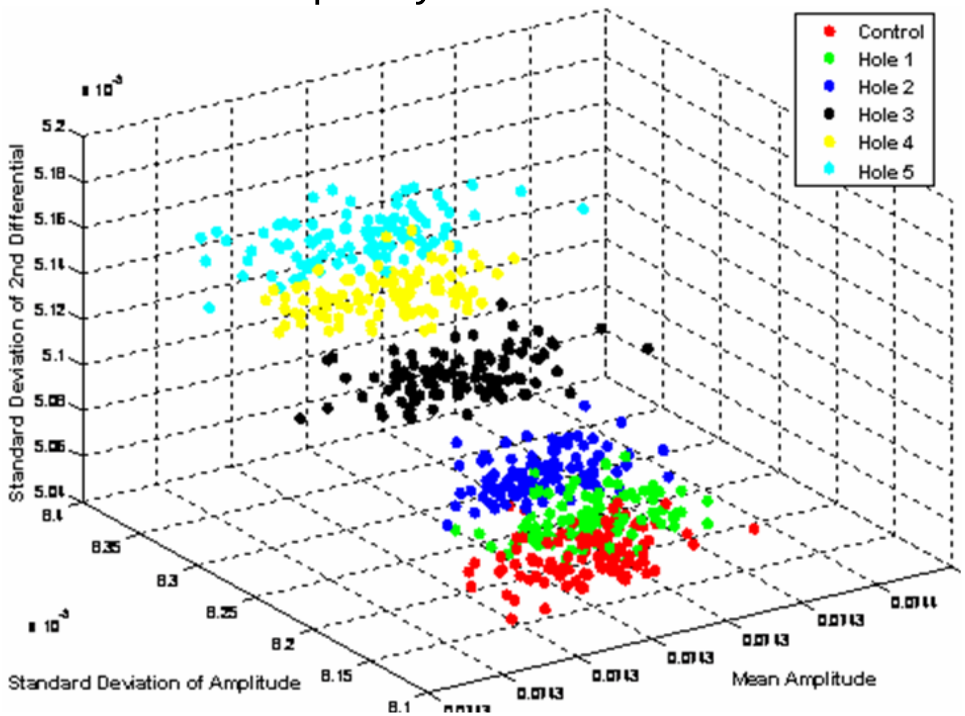
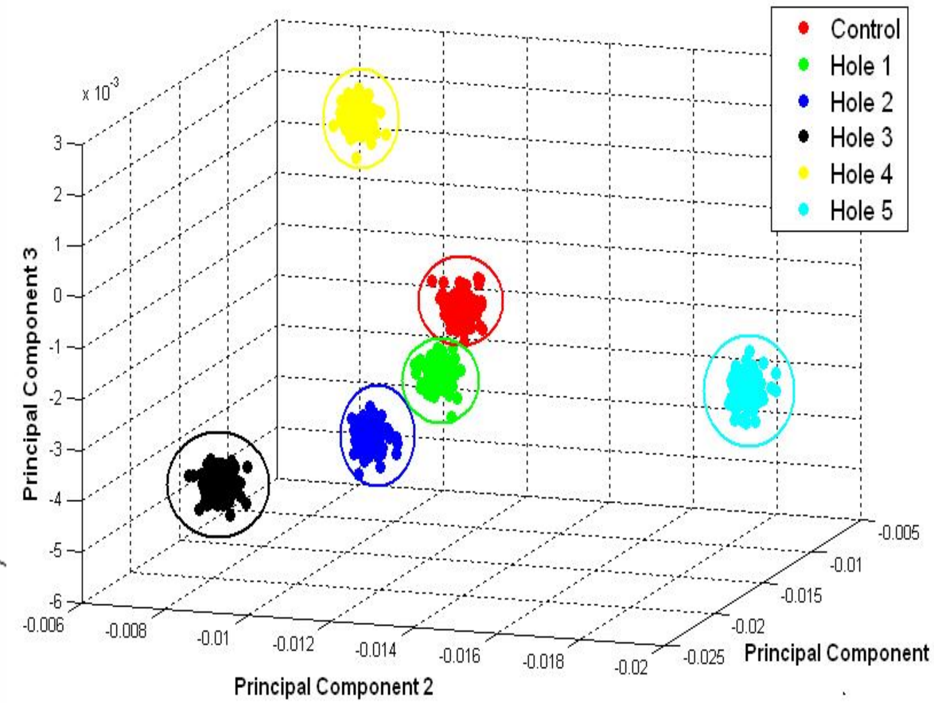
Time & frequency-based feature selection



PCA-based feature selection



- Preliminary analysis with ANOVA yielded undesirable accuracy
  - all features passed p-value test indicating viability distinguishing classes
  - although classes can be separated, cluster boundaries are diffused
- Subsequently PCA-based approach yielded improved results
  - 20 PC's represent 70% variance of 1000 point data set
  - it can be observed from 3 PC's all classes can be clearly separated

Pattern Recognition Results

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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%**

- Confusion matrix exhibits statistical accuracies KNN predictions
- 100% accuracy damage presence & type classification
- 77% severity classification, 99.9% including adjacent cells

Conclusions

- Results of PR-based methodology have been very successful
  - obtained using an optimized K-Nearest Neighbor code without logic
  - **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

Acknowledgments

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