



Design of an SHM Life-Cycle Management Software Tool

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Structural Health Monitoring (SHM)

Intelligent architecture can be designed to optimize SHM system for one or more mission roles



On-Demand NDE: In-situ inspection at fixed time or flight intervals replacing typical NDE, can enable condition-based maintenance

Real-Time Assessment: In-situ detection of impact events (bird strike, battle damage, etc.) & assessment of ability to fulfill mission



Hot-Spot Monitoring: Persistent & aggressive evaluation of failure critical or known problem areas to track present state with high precision

- SHM hardware alone not sufficient to achieve desired benefits
 - improved asset availability
 - reduced sustainment costs
- Current SHM systems provide diagnostic information (at best)
 - typically in proprietary and/or stand-alone format
 - require subject-matter experts for placement, calibration & interpretation
- For practical deployed as part of ISHM, tools must be created for SHM life-cycle management (SHM-LCM)
 - sensor placement optimization to meet architecture & POD requirements
 - algorithms calibration for specific materials & structures
 - diagnostic visualization
 - hooks to enable prognosis & action

SHM Life-Cycle Management

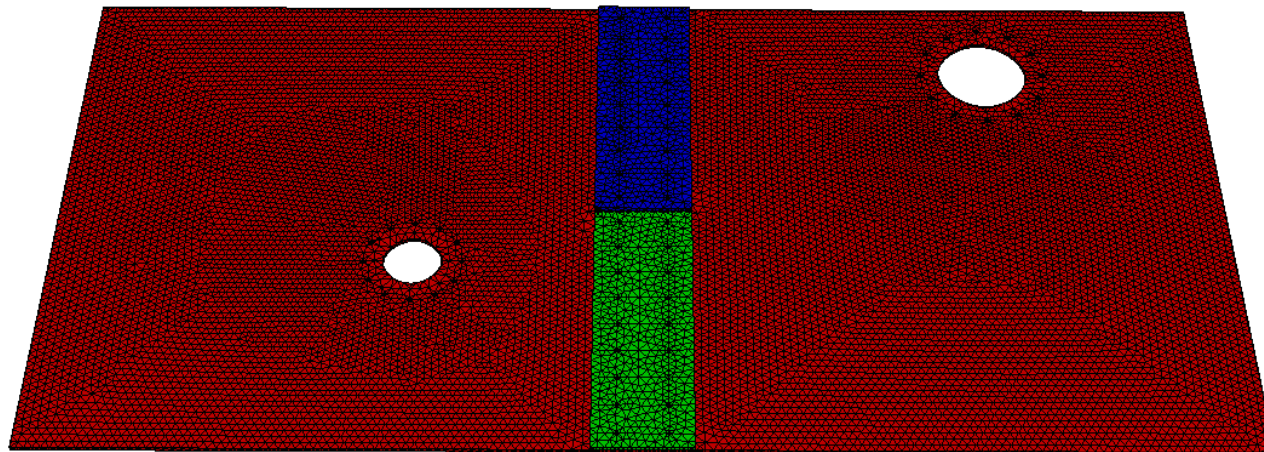


- SHM-LCM software being developed under ONR STTR funding
 - flexible application intended to manage the cradle-to-grave life-cycle
 - created to be generic & easily customized
- There are 4 core modules to facilitate critical roles:
 - **Optimization** – application-specific sensor placement
 - **Calibration** – application-specific algorithm tuning
 - **Visualization** – application-specific diagnostic data dissemination
 - **Action** – customizable tools to informed maintenance decisions
- Initial version focuses on contractor core-competencies
 - active pulse-echo style guided-wave beamforming with digital sensors
 - intent is to develop a framework that could be sensor agnostic

Optimization Module



- Optimization
 - seeks to devise optimal sensor placement & excitation parameters
 - achieve probability of detection (POD) coverage requirements
- Fueled by 3D mesh of structure to be monitored
 - user imposes POD distribution through graphical user interface (GUI)
 - resulting list of grid point to locate SHM sensors to meet requirements



Minimizing Bayes Risk



Three Basic Types of SHM Error & Their Associated Costs

Missed Detection

\$\$\$ Structural failure during operation
\$\$ Structure repair/replacement

False Alarm

\$\$ Remove system from operation
\$ Unnecessary manual inspection

Localization Error

\$ Longer inspection/structure down time
\$\$\$ Not finding damage through manual inspection

$$\text{Expected Cost (i.e. Bayes Risk)} = \sum_{\substack{\text{Types of Error,} \\ \text{Potential Damage Locations,} \\ \text{Potential Types of Damage}}} \text{Error Cost} \times \text{Error Probability} \times \text{Damage Probability} + \text{Hardware Cost}$$

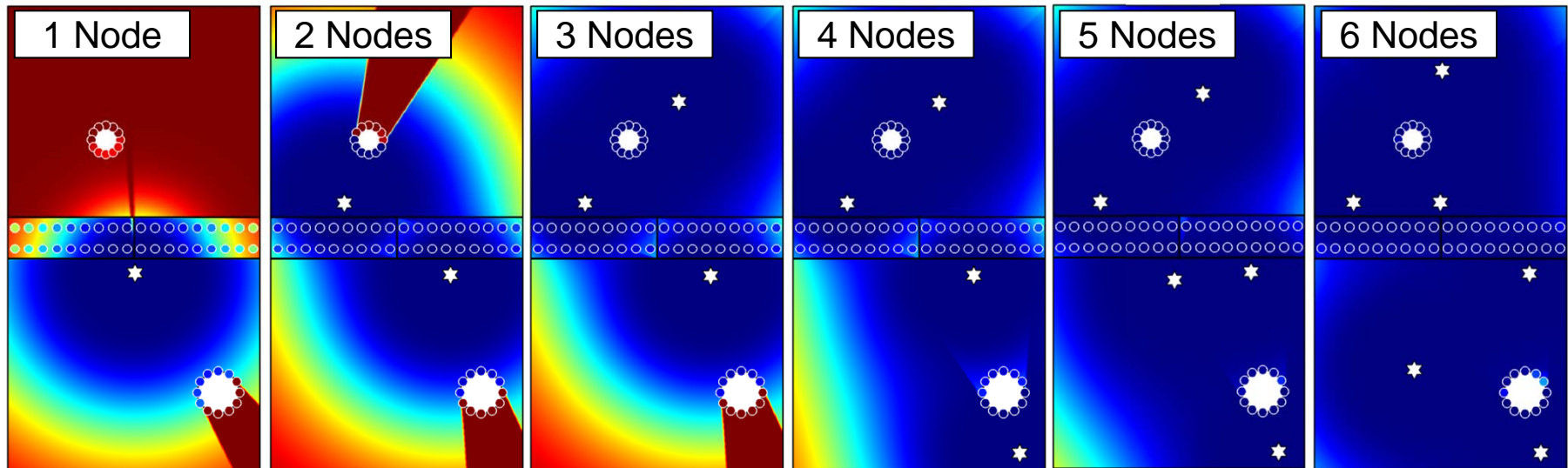
F (Hardware Design, Algorithm Design)

Two arrows originate from the text 'Optimal SHM Design:' and point to 'Error Probability' and 'Hardware Cost' in the equation above.

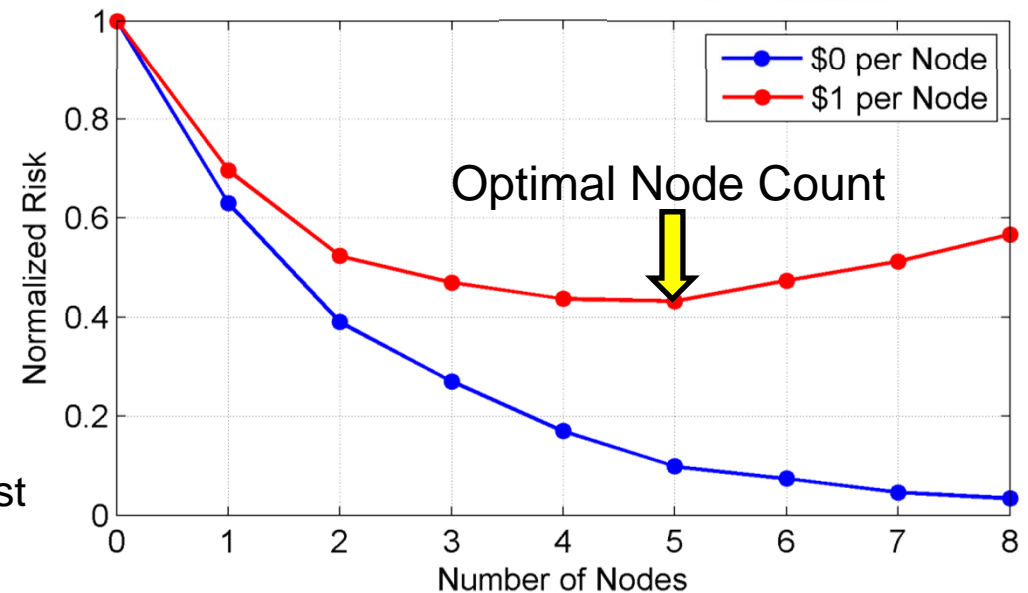
Optimal SHM Design:

Choose hardware & algorithm design to minimize Expected Cost (Bayes Risk)

Sensor Placement



- Probability of Damage: 50%
 - 37.5% @ Bolts or Holes
 - 12.5% @ Everywhere else
- Cost of Missed Detection: \$30
- Cost of False Alarm: \$30
- Localization Error: \$15 /meter
- SHM Burden: \$1 /sensor/test

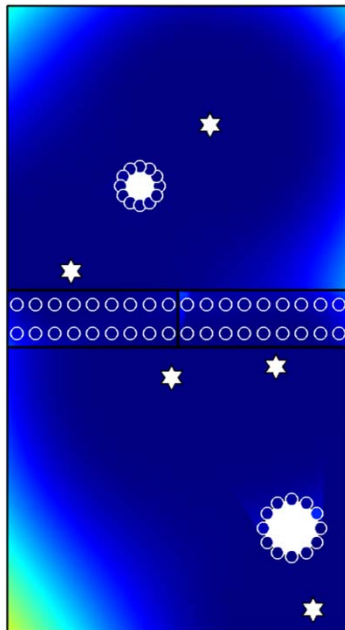


Why Defining the Problem Matters



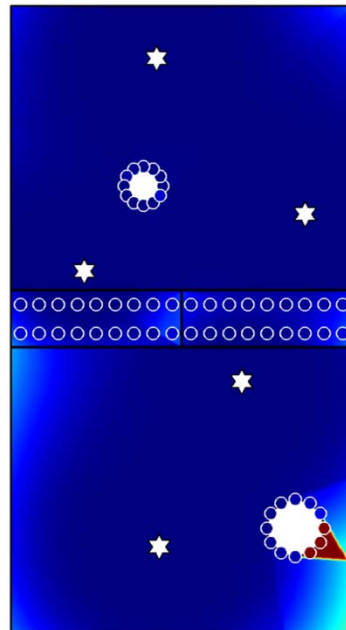
The error costs & damage probabilities **drive** SHM design

Design Optimized
for 75% Probability
of Damage @
Bolts or Holes

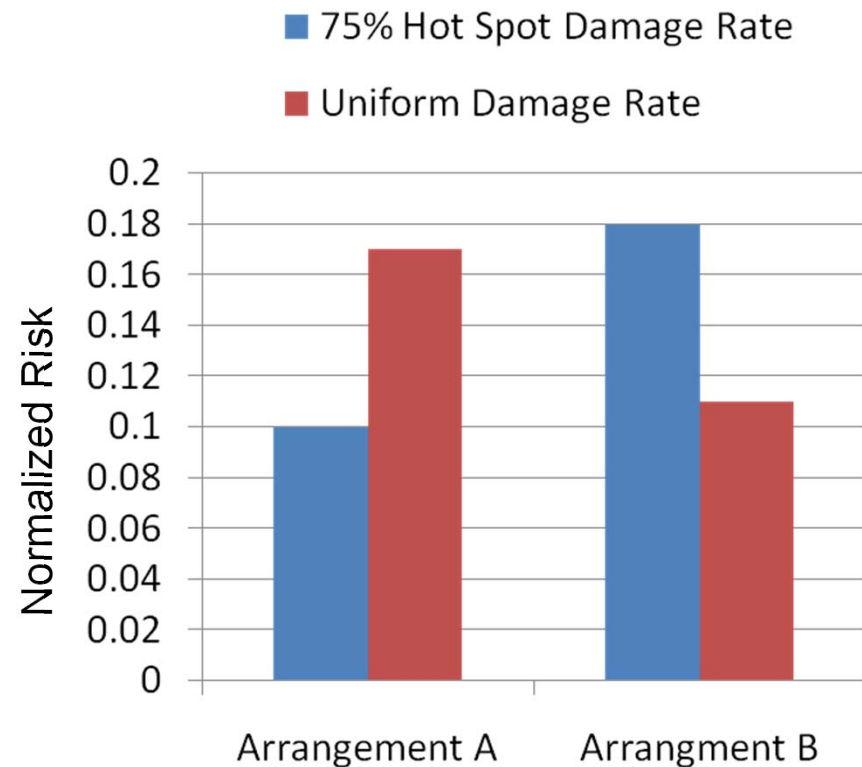


Arrangement A

Design Optimized
for Uniform
Probability of
Damage



Arrangement B

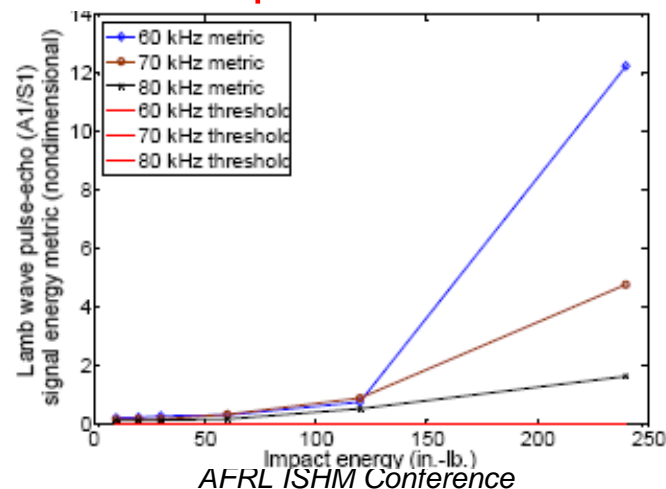


**Optimizing for the wrong specs:
70% increase in expected cost!**

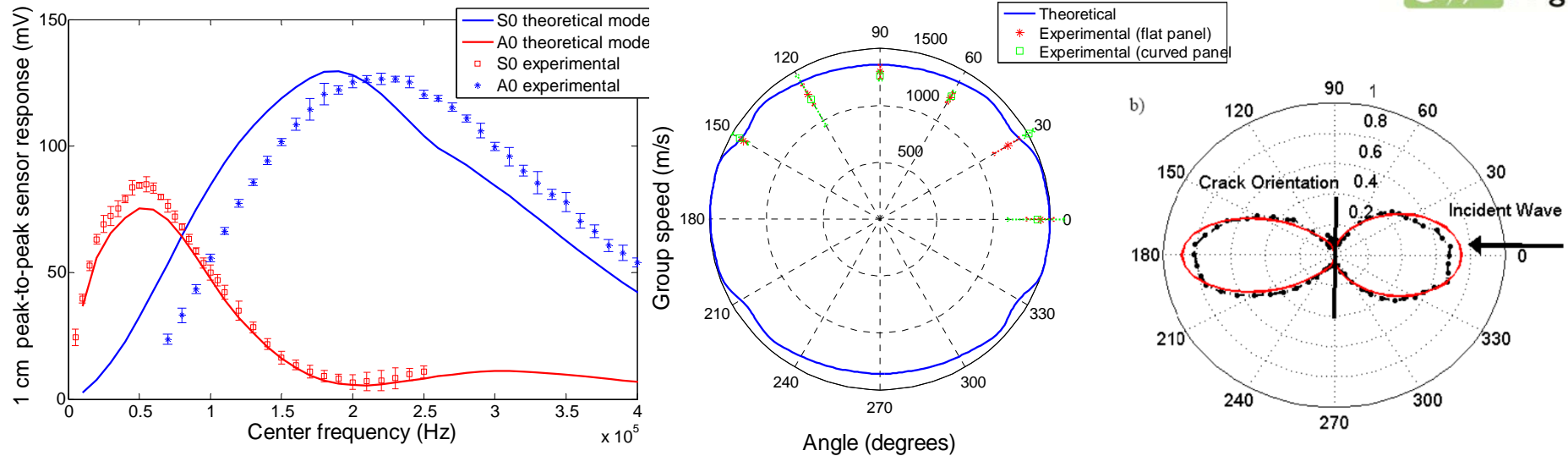
Calibration Module



- Calibration
 - customize algorithm variables to the system being designed
 - used to translate individual sensor raw data into diagnostic results
- Fueled through a series of user-guided material-level tests
 - fuse data from both active & passive sensor sources
 - diagnostic structural/sensor health, including quantified uncertainty
 - bootloader used to disseminate constants through sensor network
 - output would be a file to be uploaded onto SHM system diagnostic server



Empirical Calibration



- Experiments designed to extract relevant parameters
 - wavespeed as a function of frequency and angle
 - dissipation/attenuation as a function of frequency
 - scatter response to various damage modes
- Data used to populate algorithm constants
 - can use pure theory, but empirical data improves uncertainty
 - parameters can be stored in database and reused for similar applications

Localization Algorithms

Hybrid Coherent-Incoherent Processing:

- Phase-coherent among transducers in each node
- Phase-incoherent from node to node
- Both a function of false-positive minimizing threshold value

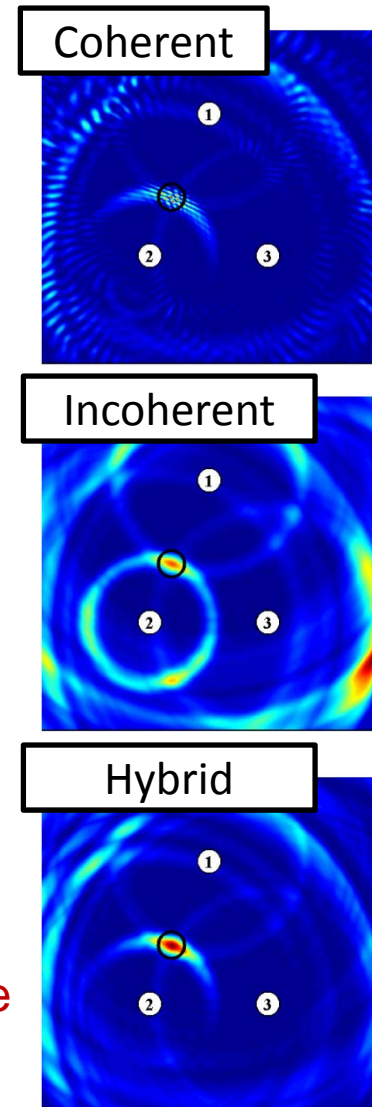
Coherently combine waveforms from transducers in each node

$$T_H(\mathbf{x}) = \left| \sum_{n=1}^N \left| \sum_{p=1}^6 w_{np} \left(t - \tau(n, p, \mathbf{x}) \right) \right| \right|$$

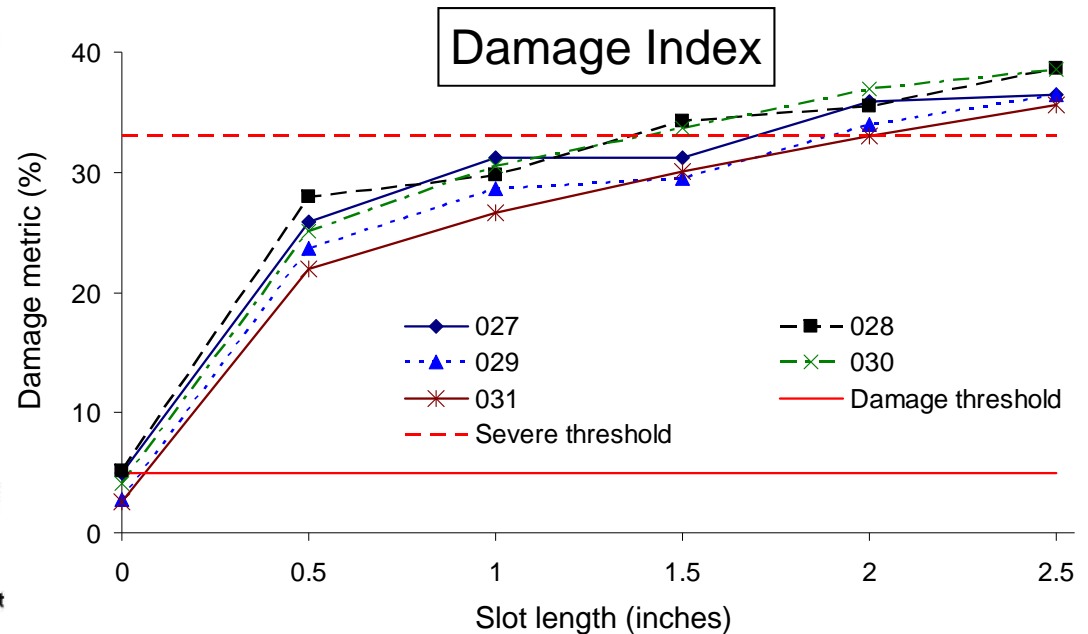
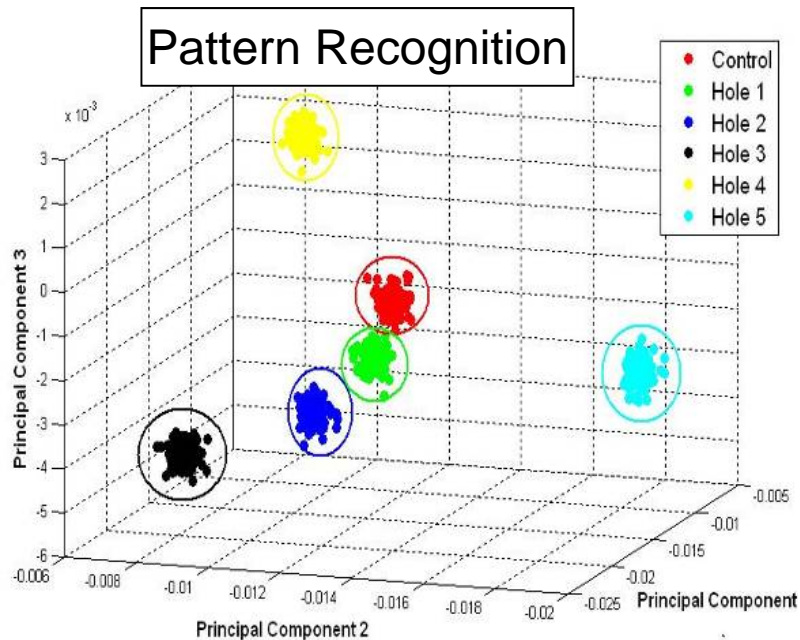
Analytic signal Time of flight to imaging point

The equation shows a double summation. The inner summation over p (from 1 to 6) is labeled 'Analytic signal' with a blue arrow pointing to w_{np} . The term $\tau(n, p, \mathbf{x})$ is labeled 'Time of flight to imaging point' with a blue arrow pointing to it. A red bracket under the entire expression is labeled 'Incoherently combine summed waveforms from each node'.

Incoherently combine summed waveforms from each node



Type & Severity Algorithms

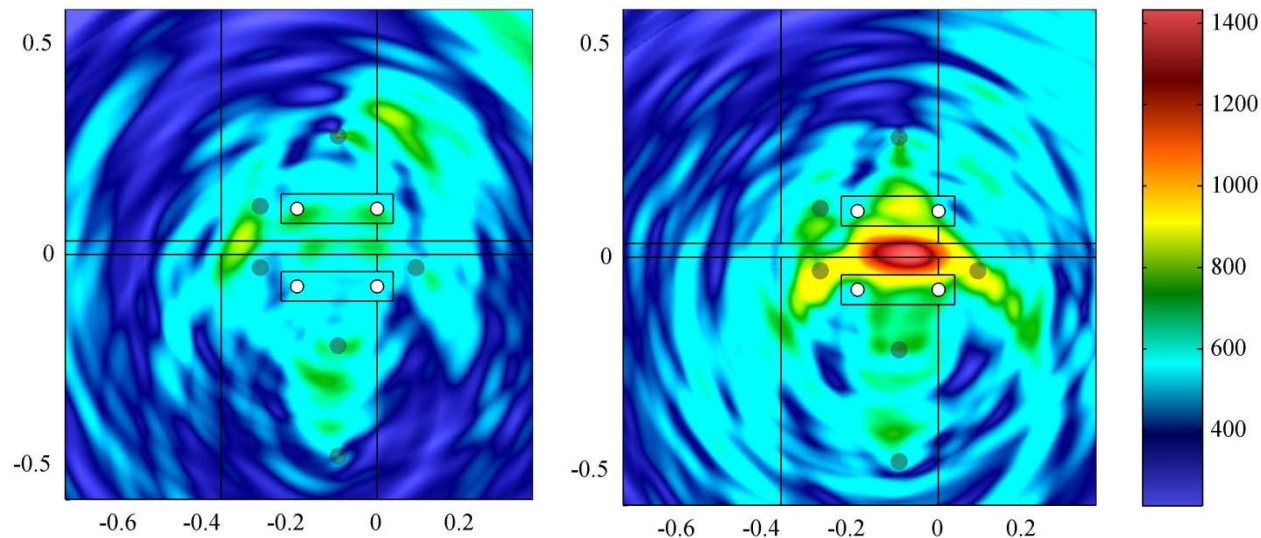


- **Pattern recognition techniques used for type discrimination**
 - have achieved repeatable results for both metal & composites
 - models have been demonstrated for reduced training set
- **Damage index used for severity classification**
 - have shown success in composite, metals and hybrid materials (GLARE)
 - demonstrated blind fatigue crack resolution as small as 0.1 mm in Ti

Visualization Module

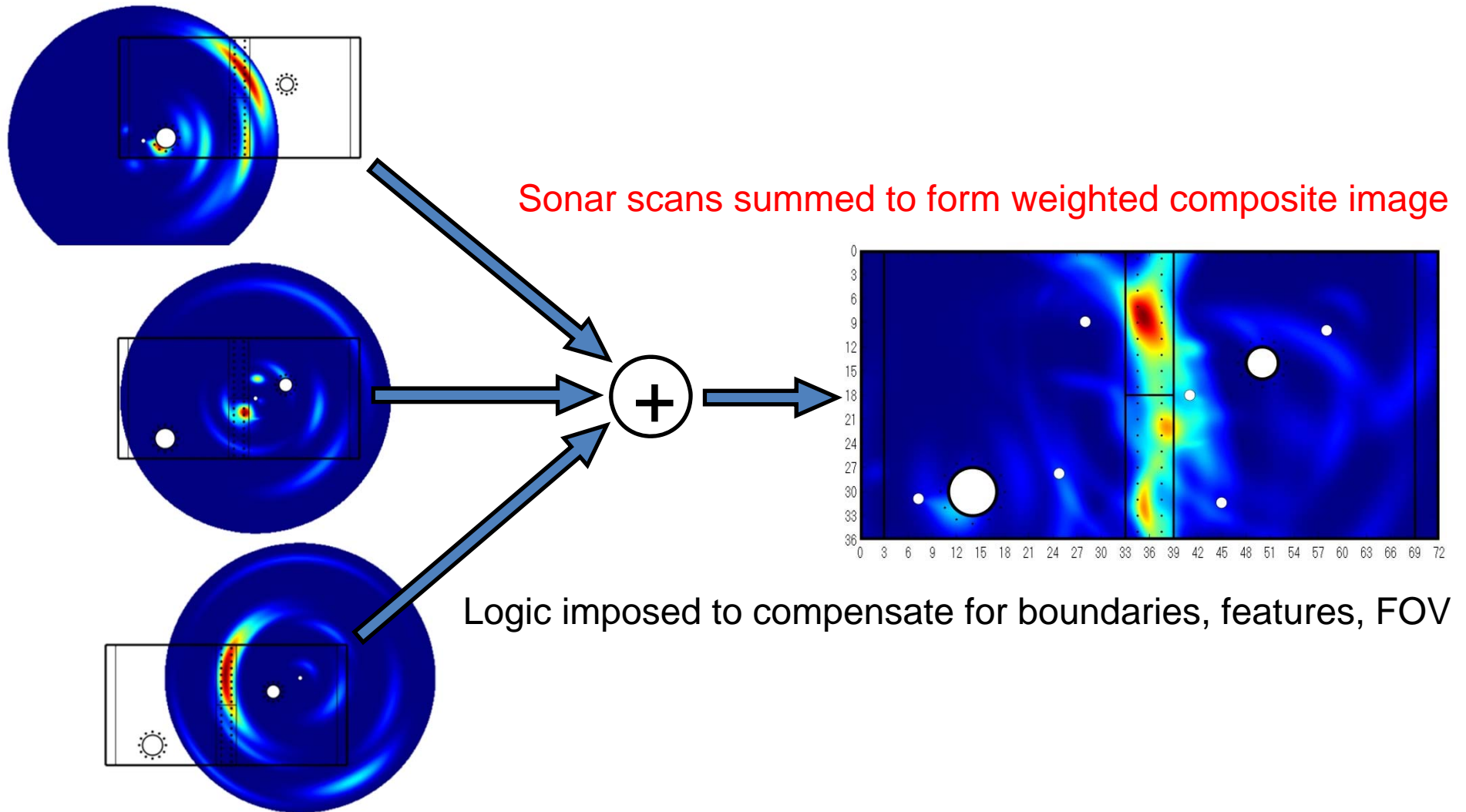


- Visualization
 - generates a diagnostic composite picture for the application
 - stitched to original 3D mesh
- Fueled by data downloaded from diagnostic server
 - output provides users with manipulatable GUI (zoom, rotate, x-section)
 - toggle between probability of damage for various calibrated modes
 - can update mesh for residual prognostic analysis (untied nodes, etc)

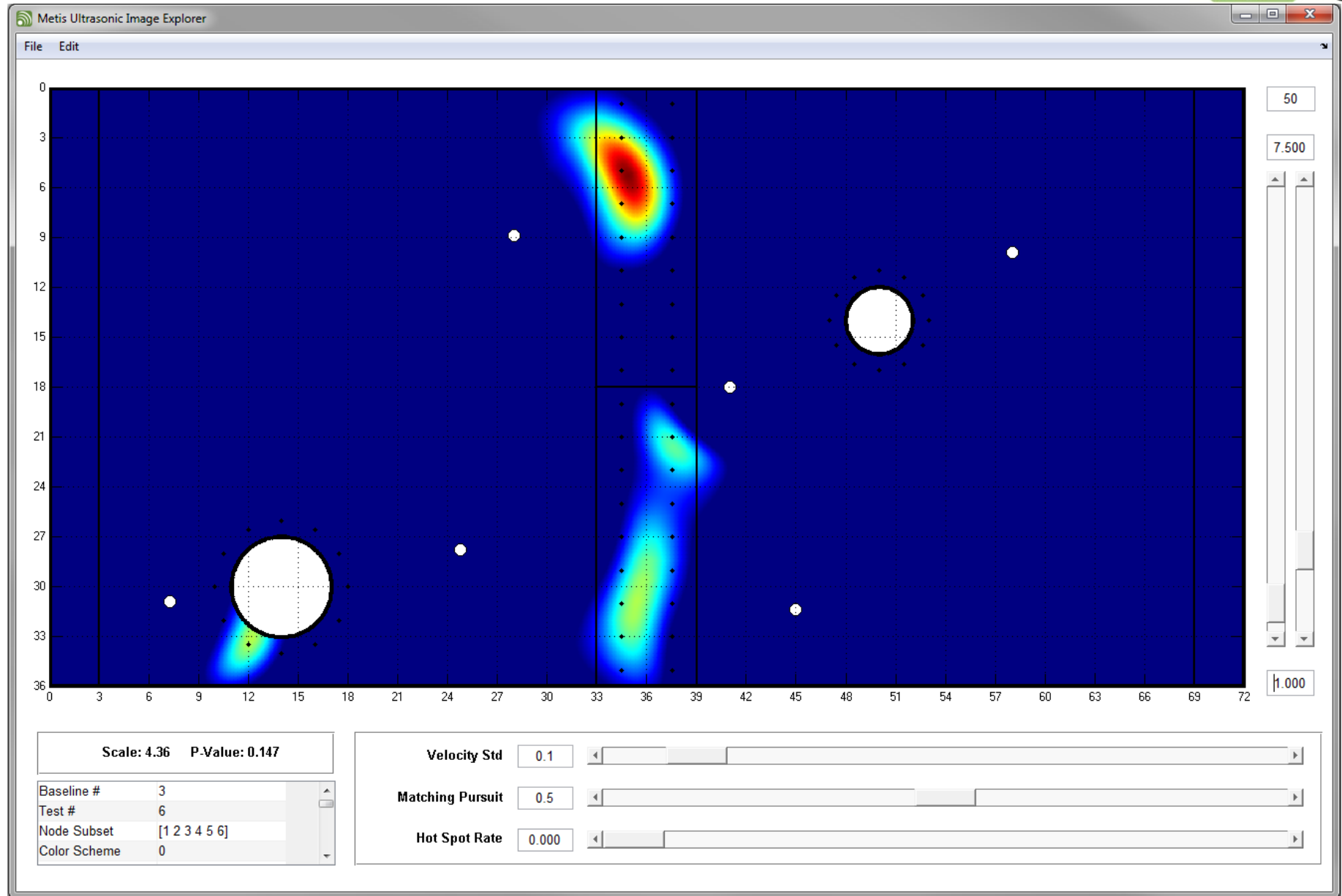


Data Analysis & Reconstruction

Each node processed individually to provide location-independent sonar-scan



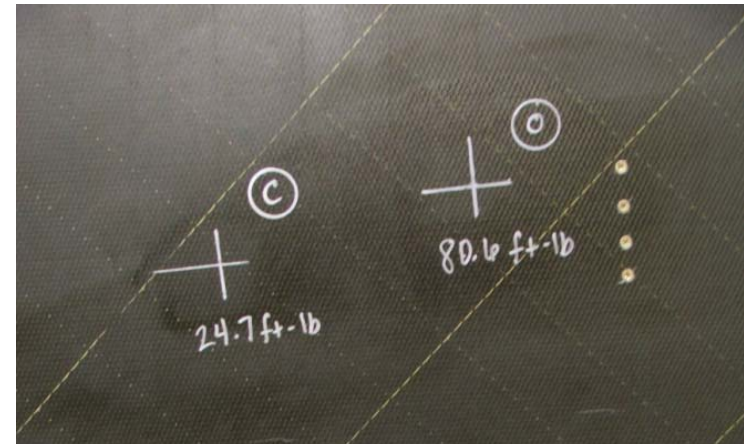
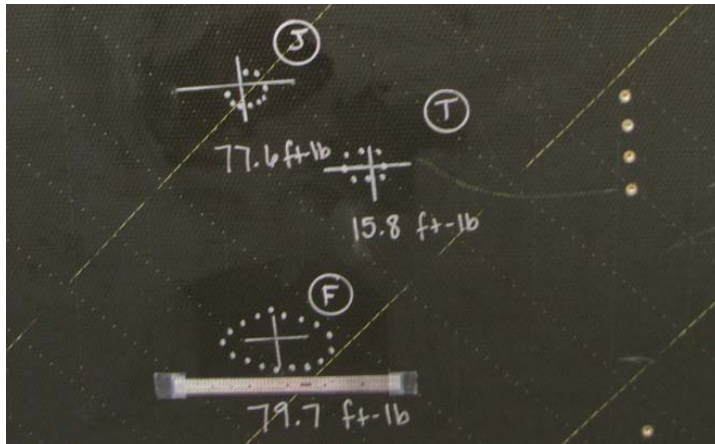
Diagnostic Visualization



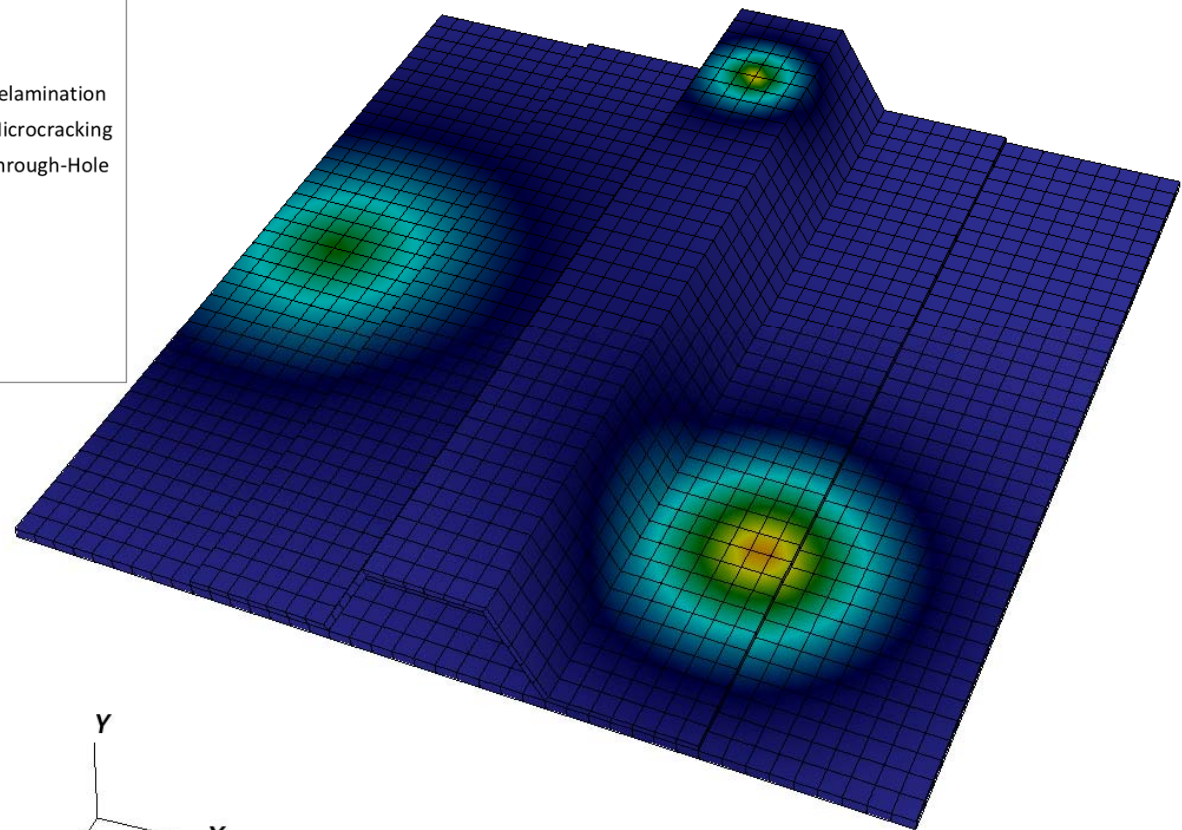
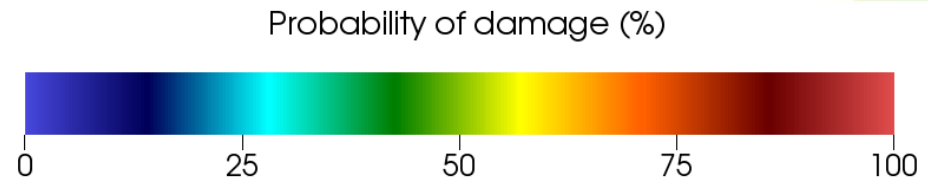
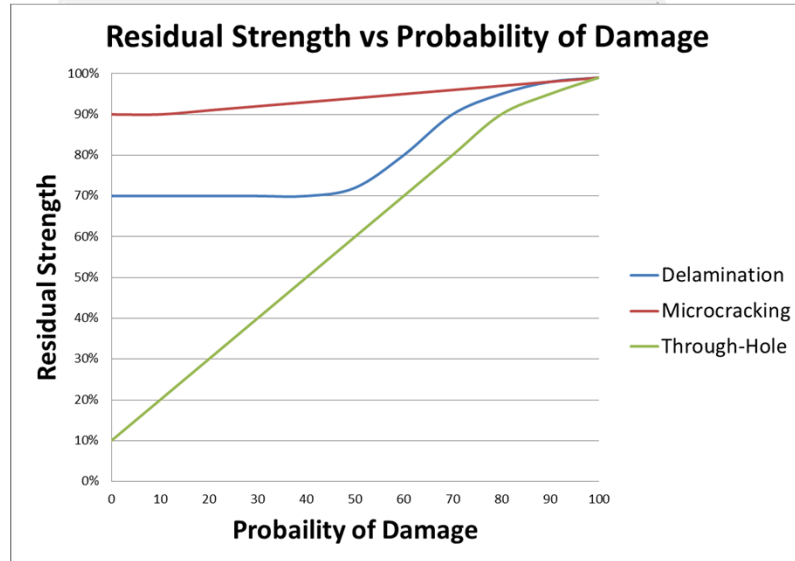
Action Module



- Action
 - provides users with guides for responses to the diagnostic results
 - allows users to weigh detection confidence against impact to capabilities
- Fueled by analytical comparison of baseline/diagnosis
 - residual performance plots as a function of probability of damage
 - could enable fly-by-feel methodologies for adaptive control
 - repair optimization plug-in for restoring original performance level
 - could be local data accumulator or card in a HUMS or AHM system box



Diagnostics to Prognostics



☒ Apply operators / ☒ selection to all plots

Pick

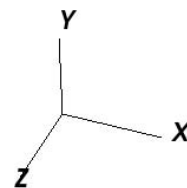
A

```
C:\Program Files\VisIt\Ansys4.vtk timestep 4  
mesh  
Point: <0.0502083, 0.00275, 0.0497648>  
Zone: 2189  
Incident Nodes: 2738 2739 2778 2777 4132 4133  
4172 4171  
damage: <nodal>  
(2738) = 74.701  
(2739) = 84.4309  
(2778) = 86.8063  
(2777) = 75.7949  
(4132) = 72.3809
```

Max Tabs

8

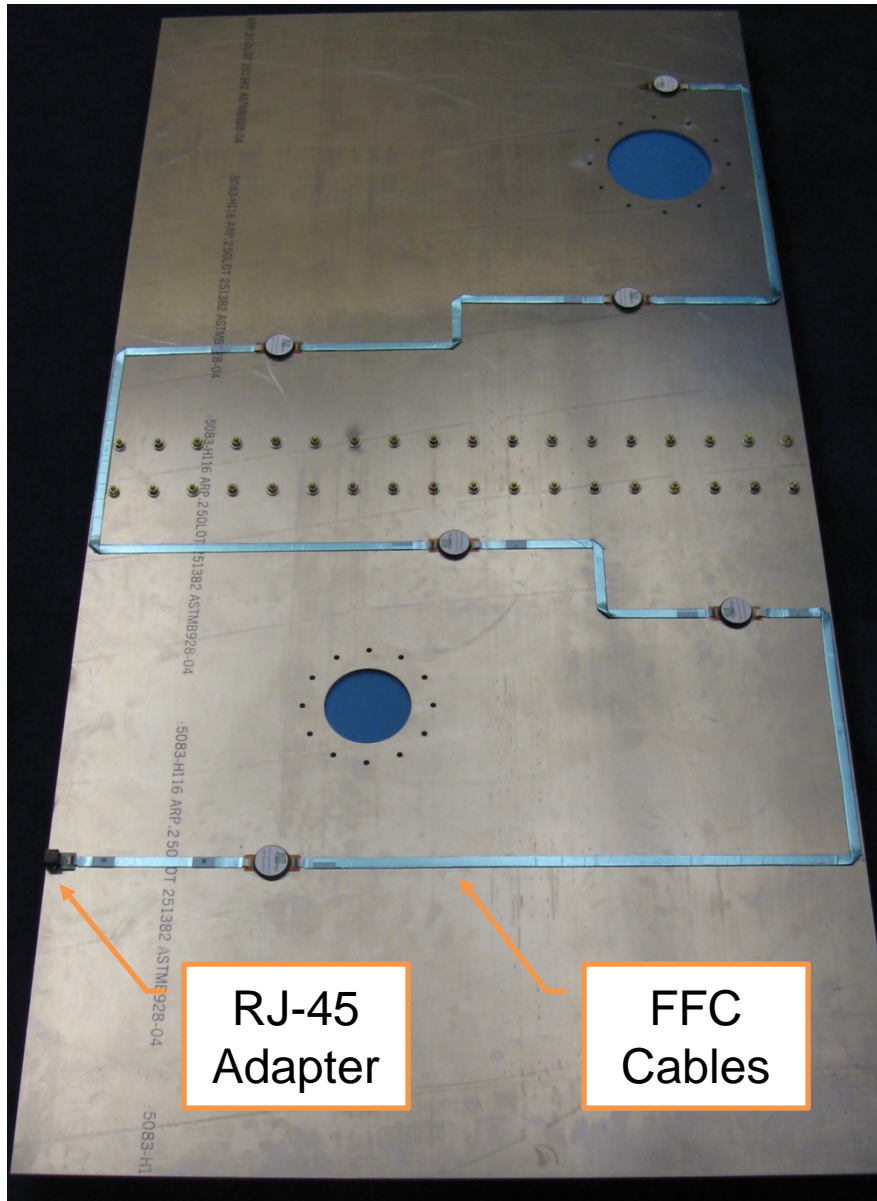
Save Picks as...



0.00" 0.25" 0.50" 0.75" 1.00"

Damage size

Prototype Example Problem



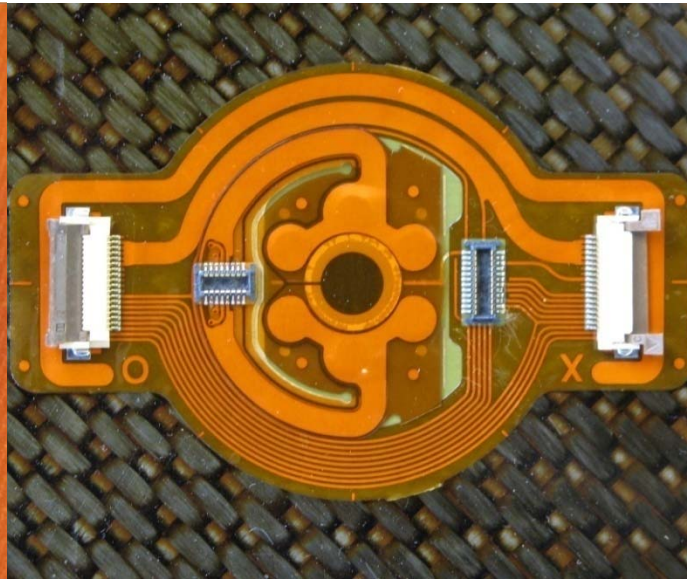
MD7 Digital SHM System



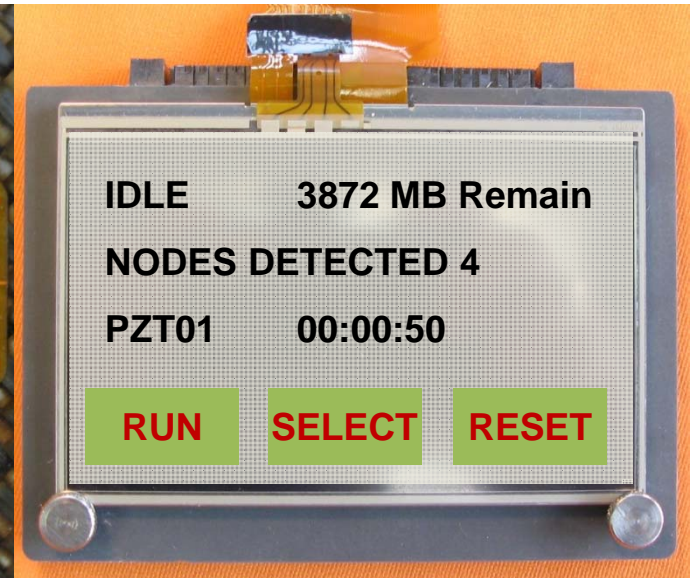
MD7 IntelliConnector™



MD7 VectorLocator™



MD7 HubTouch™



- IntelliConnector™ (digital element)
 - provides excitation, data acquisition, some signal processing
- VectorLocator™ (analog element)
 - contains 6 PZT sensor elements & 1 PZT actuator to form 1 SHM node
- HubTouch™ (network element)
 - drives data bus, commands testing, synchronizes nodes, stores data

Placement Optimization



- 6 SHM nodes in optimized locations
 - minimized Bayesian risk used
 - assumed more damage at holes/bolts
 - “greedy” approach to analyze 4-6 nodes
- System installation before shipping
 1. FFC mounted w/semi-permanent tape
 2. VectorLocator flex bond w/AE-10
 3. IntelliConnectors bond w/5-min epoxy

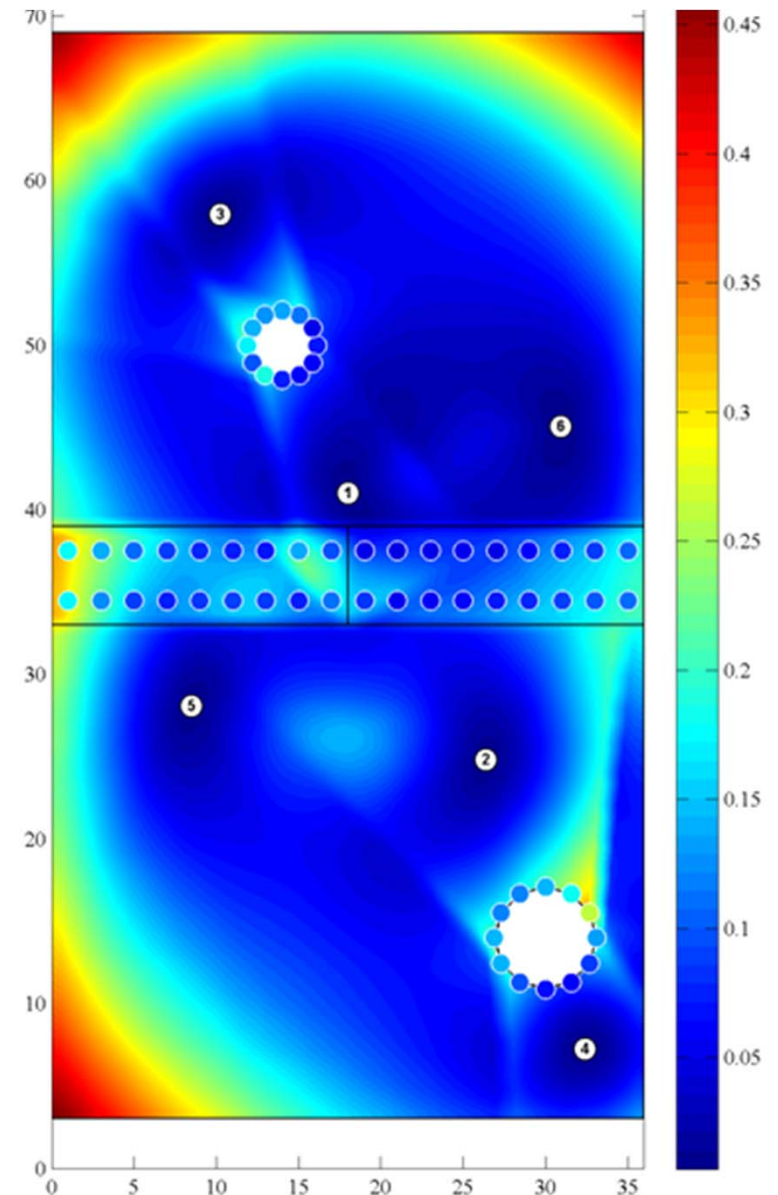
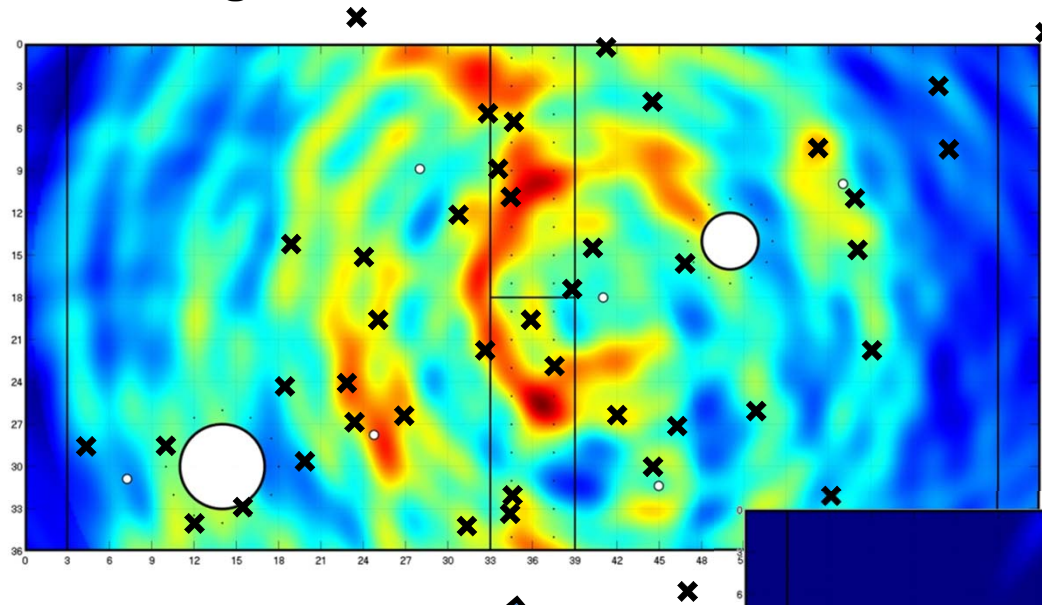
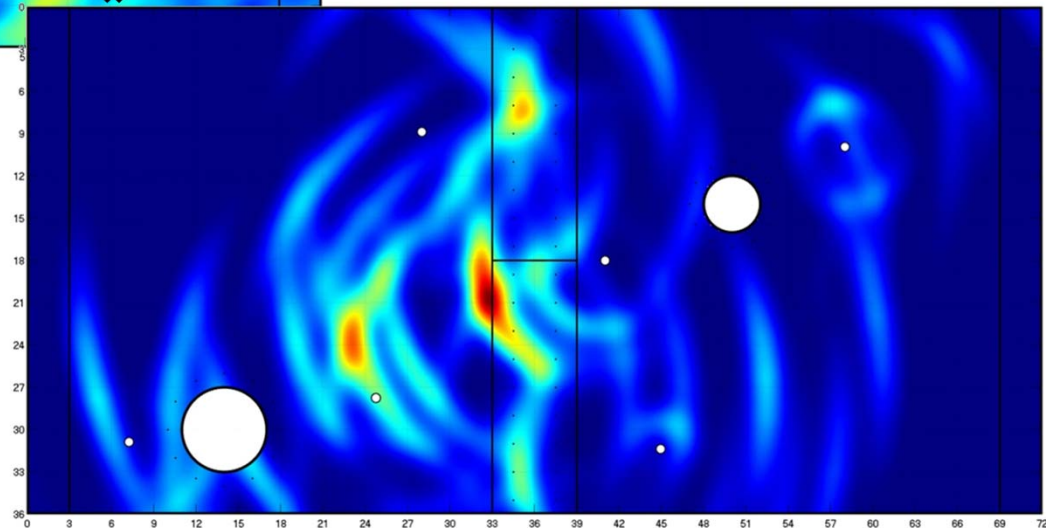


Image Processing

Raw Image with Identified Scatter Sources using Matching Pursuit



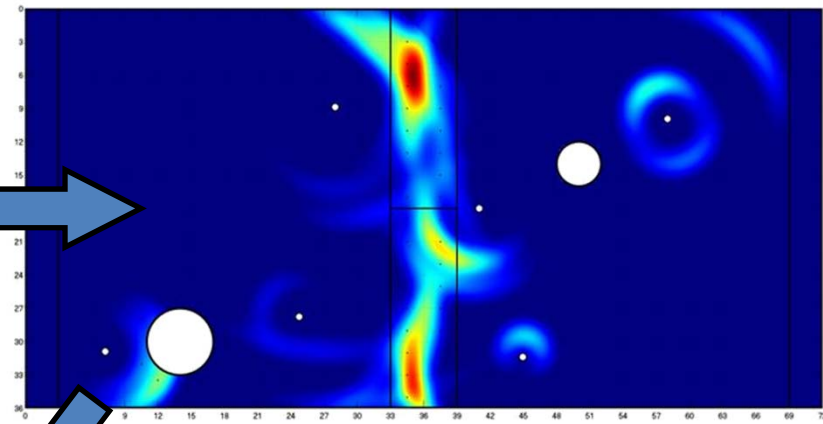
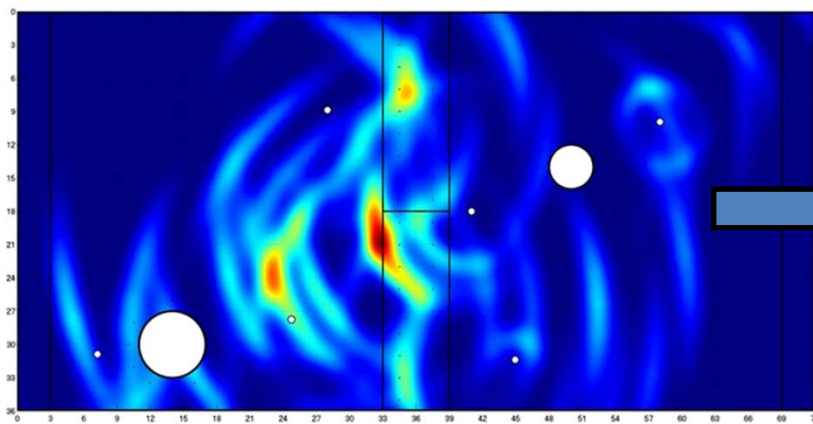
**Narrow the angular width
of the scatter sources in
the reconstructed image**



Visualization Options

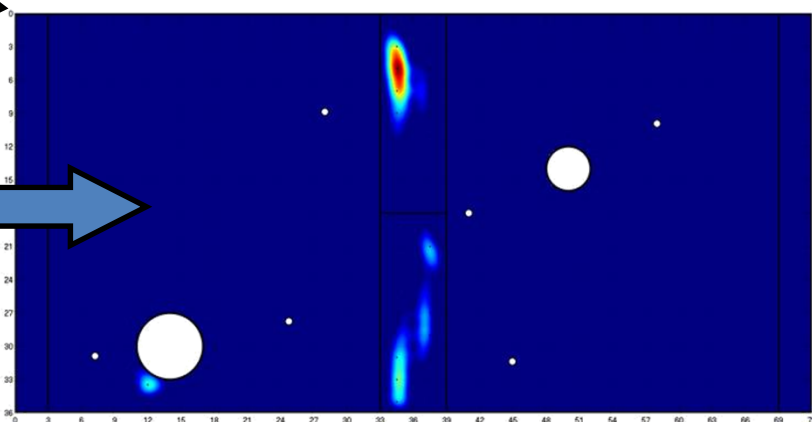
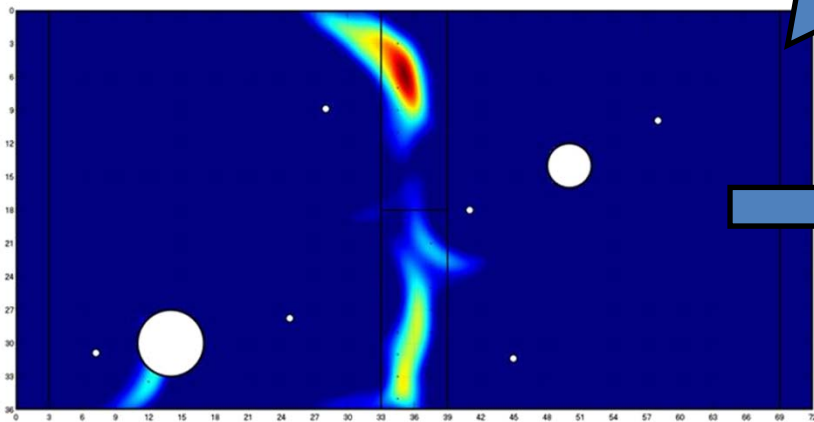
Reconstructed Image

Filter impossible scatter sources (line of site, etc.)



Normalize by sensor noise floor

Apply prior probabilities*



* Only if applicable

Overall Vision



- SHM-LCM stool aims to make technology more accessible
 - enables non-expert engineers to design & use SHM systems
 - reduce cost/time of platform implantation, more commercially practical
 - **envision tool used just like FEA is used today to certify structural designs**
- Visualization tool aligns well with Navy strategies/initiatives
 - **NDE-like interface eases transition, eliminate manual probes & teardown**
 - toggle between damage modes to view diagnostic probabilistic results
 - integrate with FEA for residual performance vs damage probability plots
 - integrate with optimization tools for repair patch recommendation
- Sponsored by ONR, Littoral Combat Ship (LCS) program
 - presently participating in large scale testing of ship aluminum deck
 - intend to participate in sea-trials in late 2011 or early 2012

Acknowledgments



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