SAM-P1.10:
Sparsity, Super-Resolution and Imaging

Anomaly Imaging For Structural Health Monitoring Exploiting Clustered Sparsity

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Objective: Anomaly Mapping

Anomaly indices computed from sensor measurements → ? → Color map indicating damages on structure

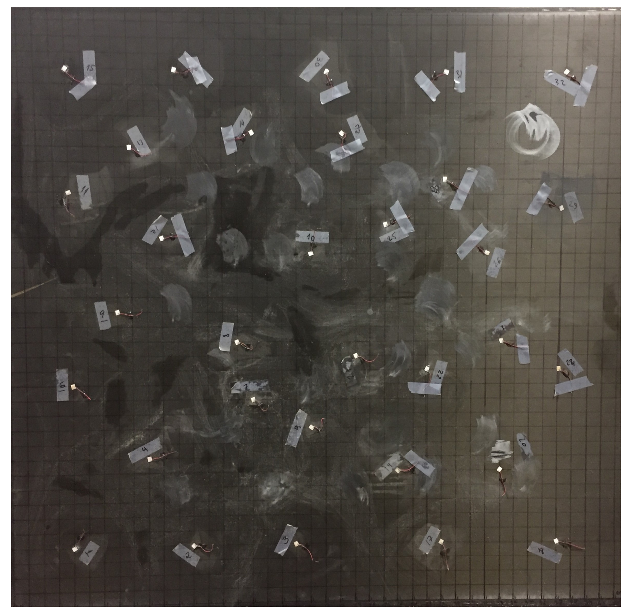
Applications

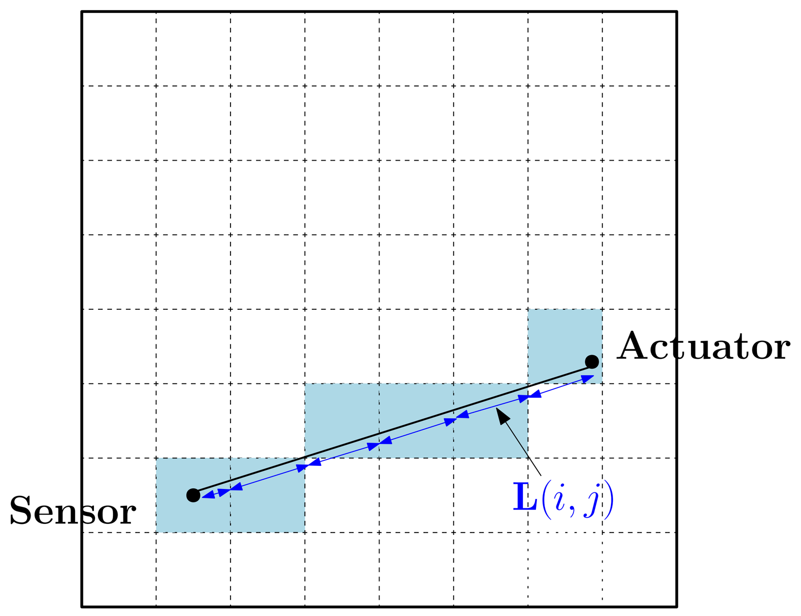
- Aircraft
- Load bearing walls
- Oil pipelines

System Model

Setup

- m piezoelectric transducers equipped on the structure
- One measurement for every transducer pair





Grid based reconstruction

- Spatially continuous map is discretized into N pixels

Damage indices model: $\mathbf{y} = \mathbf{L}\mathbf{x}$
Problem: Estimation of discrete map $\mathbf{x}$

Central Idea: Map is Block-sparse

Sparsity: Anomaly area $\ll$ overall structural area
Clusters: Anomalies occupy continuous regions

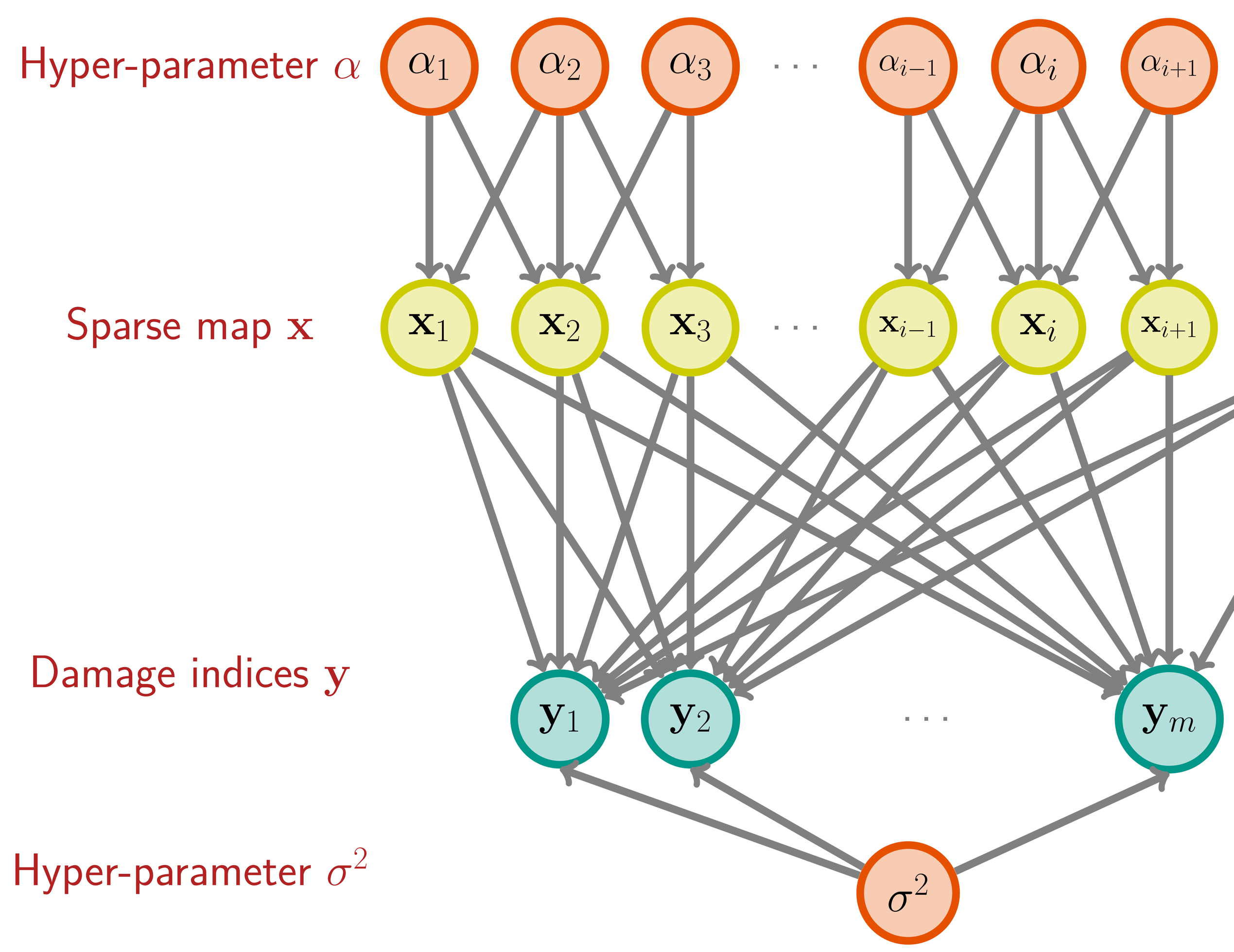
Challenge: Unknown block boundaries

Mapping Algorithm: Pattern-coupled Sparse Bayesian Learning[1]

- Impose a fictitious prior on the sparse vector:

$$\mathbf{x} \sim \mathcal{N}(0, \text{diag}\{\gamma\}) \qquad \gamma_i^{-1} = \alpha_i + \beta \sum_{j \in \mathcal{B}(i)} \alpha_j$$

- Unknown nonnegative hyperparameters: α
- Unknown noise variance: σ^2
- Learn α, σ^2 using the expectation-maximization



E-step: Discrete map $\mathbf{x}$ estimation

$$\gamma_i = \left(\alpha_i^{(r-1)} + \beta \sum_{j \in \mathcal{B}(i)} \alpha_j^{(r-1)} \right)^{-1}$$

$i = 1, 2, \ldots, N$

$$\mathbf{\Sigma} = (\sigma^{-2(r-1)} \mathbf{L}\mathbf{L}^{\mathsf{T}} + \text{diag}\{\gamma\})^{-1}$$

$$\mu = \sigma^{-2(r-1)} \mathbf{\Sigma} \mathbf{L}^{\mathsf{T}} \mathbf{y}$$

M-step: Estimate hyperparameters α, σ^2

$$\sigma^{2(r)} = K + 2c\left(2d + \|\mathbf{y} - \mathbf{L}\mu\|^2 + \text{Tr}\left\{\mathbf{L}\mathbf{L}^{\mathsf{T}}\mathbf{\Sigma}\right\}\right)^{-1}$$

$i = 1, 2, \ldots, N$

$$w_i = \mu_i^2 + \mathbf{\Sigma}_{ii} + \beta \sum_{j \in \mathcal{B}(i)} \mu_j^2 + \mathbf{\Sigma}_{jj}$$

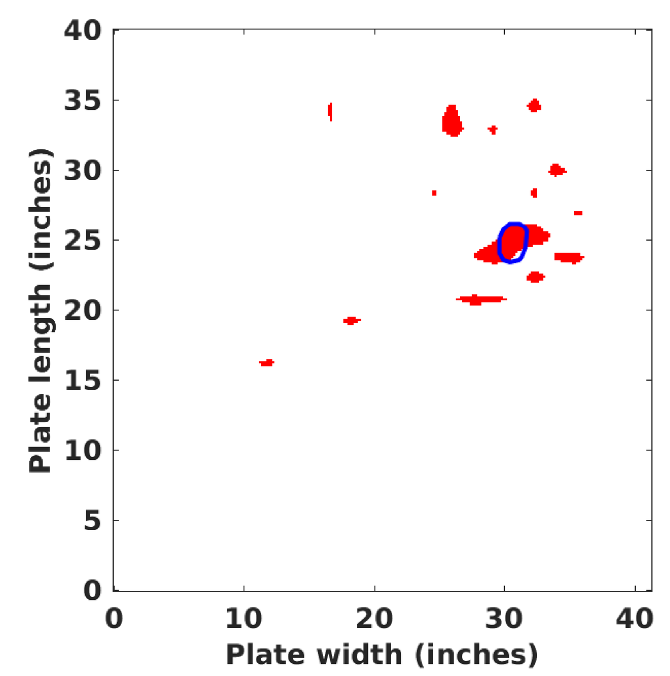
$$\alpha_i^{(r)} = 2\left(\mu_i^2 + \mathbf{\Sigma}_{ii} + \beta \sum_{j \in \mathcal{B}(i)} \mu_j^2 + \mathbf{\Sigma}_{jj}\right)^{-1}$$

[1] J. Fang, et al., "Pattern-coupled sparse Bayesian learning for recovery of block-sparse signals," IEEE Trans. Signal Process., Jan. 2015

Experimental Results

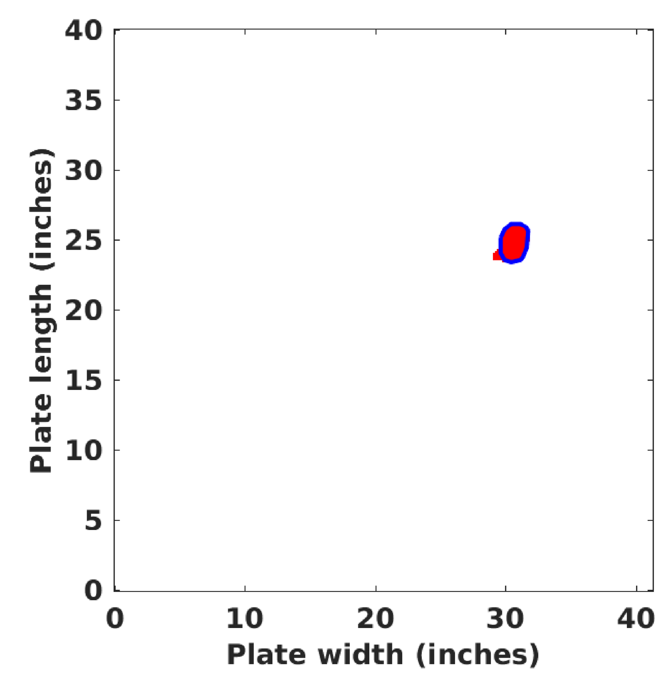
Structure	$41'' \times 40'' \times 0.1''$, unidirectional composite panel made out of 8 IM7/8552 carbon fiber plies
Transducers	Thirty two piezoelectric transducers attached to the plate covering the middle $33'' \times 32''$ region of the plate
Excitation and sampling	Linear chirp with bandwidth [150,300 kHz] collected at a sampling rate of 2×10^6 samples/second
Damge index	Computed using the extracted first arriving mode of the measured signal and the baseline signal
Anomaly boundaries	Locations on the structure where the estimated map value was greater than a threshold

Exploiting no structure



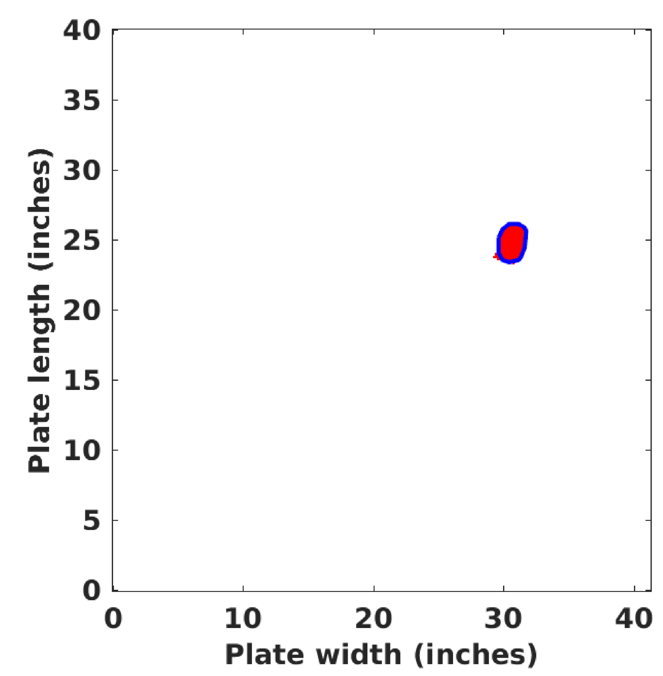
SD index = 0.3427

Exploiting sparsity only



SD index = 0.9005

Exploiting clustered sparsity



SD index = 0.9377

Summary

Goal: Estimate the anomaly map from sensor-actuator measurements
Algorithm: Pattern-coupled sparse Bayesian learning which accounts for block sparsity
Validation: Using a data set obtained from impact experiments

Take Home Message
Exploiting any known underlying structure of the damage improves the map reconstruction accuracy

Financial Assistance