Integrated Fusion, Performance Prediction, and Sensor Management for Automatic Target Exploitation

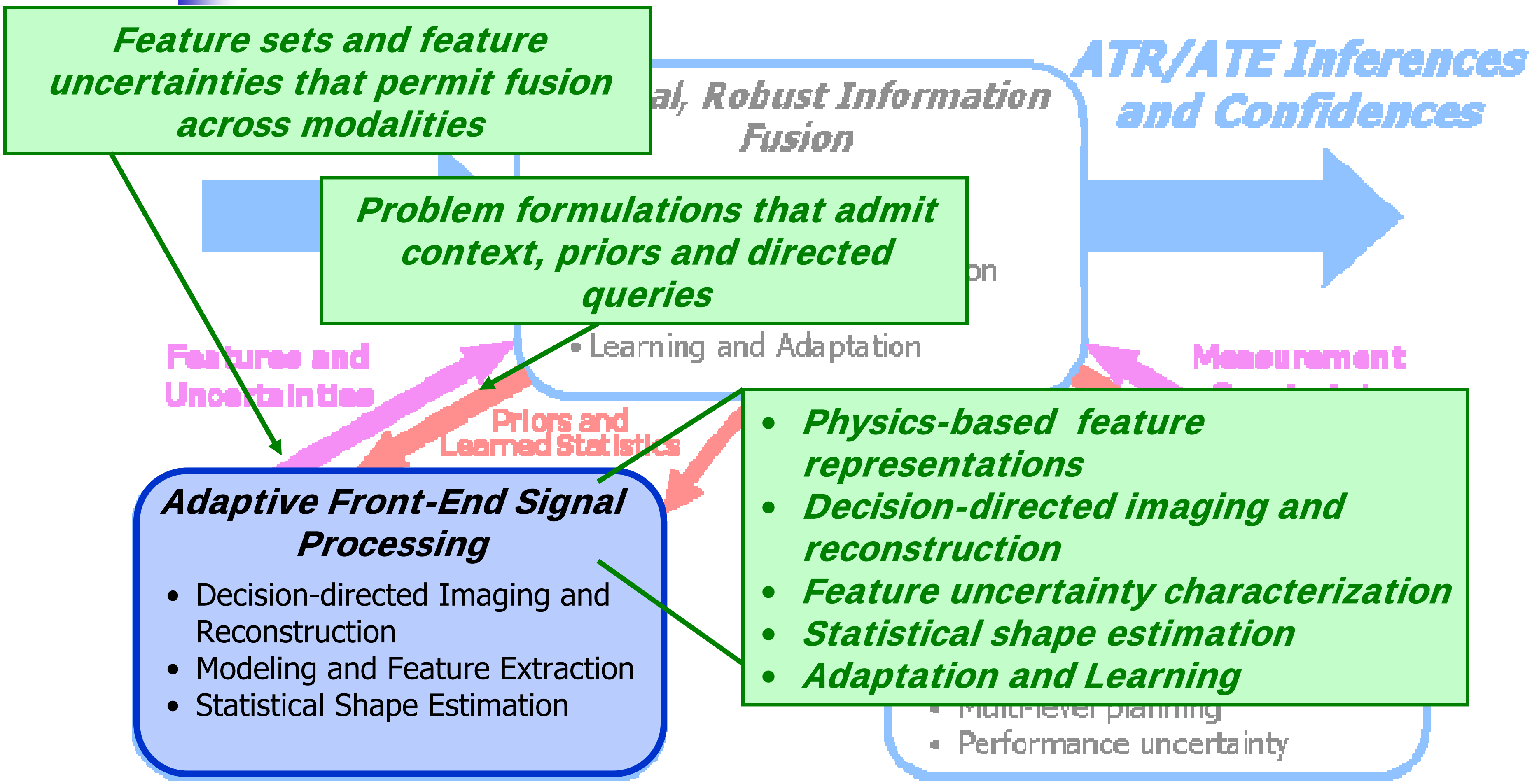
Inference-Aware Feature Extraction and Reconstruction

MURI Review Meeting

Müjdat Çetin, Emre Ertin, Al Hero,
Clem Karl, Randy Moses, Lee Potter

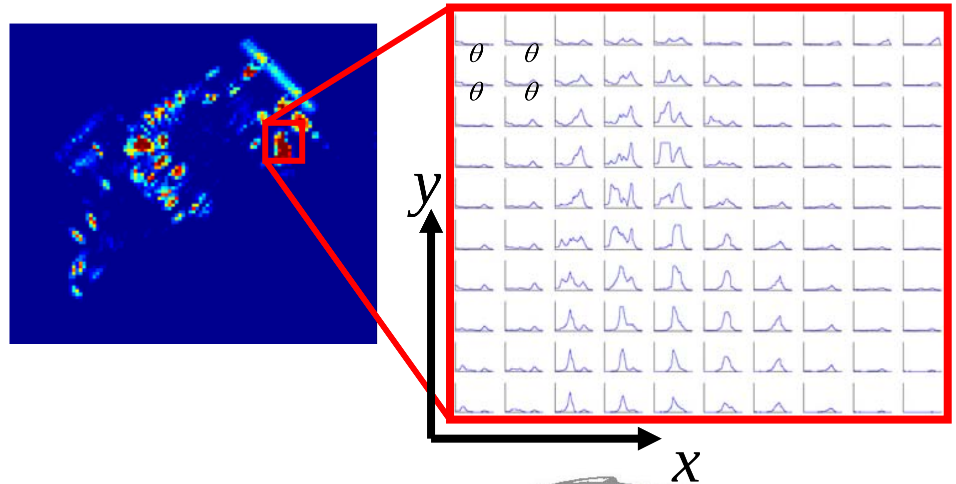
November 3, 2008

Processing with purpose

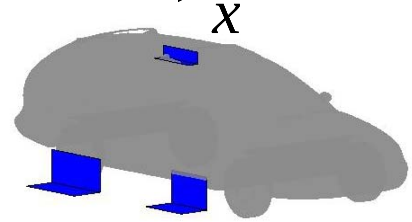


Where were we last time?

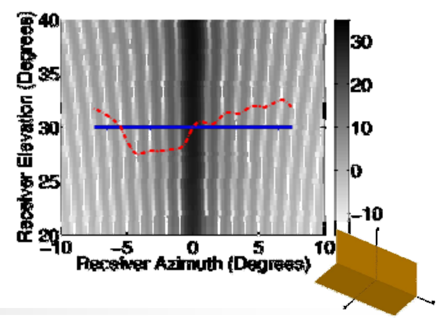
- Sparseness v. sparseness
  - Sparse apertures
  - Sparse signal representations
  - Complexity reduction



- Physics-driven basis sets
  - Use prior information in basis sets
  - Extract object-level information



- Physical optics for model-based imaging
  - 3D
  - Sparse apertures



New work in 2008: Themes

- Expanding the envelope
  - Multistatic imaging of movers *no bandwidth, no problem*
  - Multipass 3D imaging *IFSAR on steroids*
  - Recursive imaging *persistent surveillance made easy*
  - Joint mo-comp and imaging *exploiting sparsity*
  - Hyperspectral *moving beyond RF*

- Balancing models and measurements
  - Stein's unbiased risk/L-curve *selecting hyperpara*
  - ML estimation *empirical Bayes*

- Closing the loop
  - Sensor placement *utility metric for contro*
  - Posterior probabilities *the language for fu*
    - Hyperspectral
    - Sparse imaging

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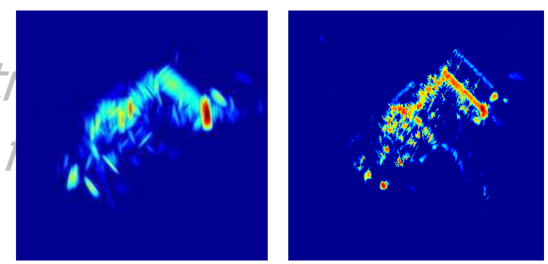

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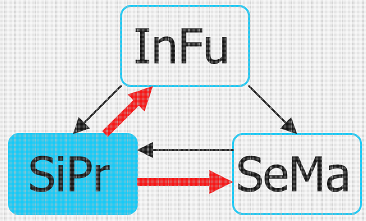


Tour de MURI

- Multistatic radar imaging (Clem)
- Hyperspectral demixing (Al)
- Bayesian matched pursuits (Lee)
- Sparse + hyperparams + mocomp (Mujdat)
- Multipass 3D (Emre)
- Recursive SAR imaging (Randy)

Multistatic imaging

Karl

- Sparsity-based reconstruction
- Closing the loop: aperture utility metric
- Imaging moving targets

Multistatic Radar

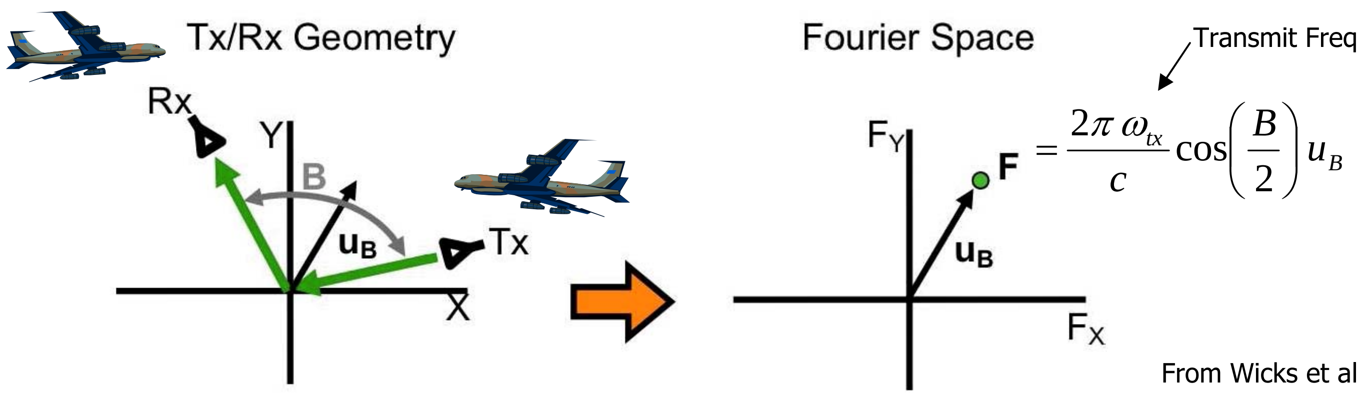
Karl

- Sensing Model

$$y_{\mathbf{rx}_i,\mathbf{tx}_j}(t) = \iint_{|\mathbf{r}|\le L} f(\mathbf{r}) \exp^{-jK(t)[(\mathbf{s}_{\mathbf{rx}_i} - \mathbf{s}_{\mathbf{tx}_j})\cdot\mathbf{r}]}\, d\mathbf{r}$$

Reflectivity | Tx frequency | Tx/Rx geometry

- Different choices for K(t), rx, tx possible



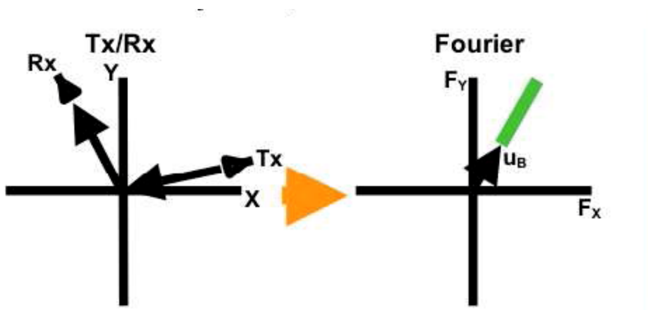
B = bistatic angle
u_B = bistatic bisector
ω_{tx} = transmitted frequency

MURI: Integrated Fusion, Performance Prediction, and Sensor Management for Automatic Target Exploitation

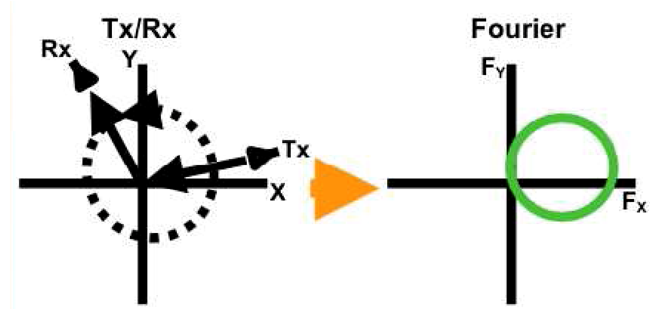
Many Sensing Options…

Karl

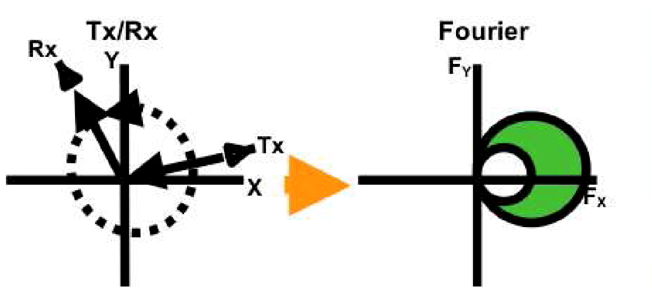
Case 1: Stationary Tx/Rx, Wideband waveform



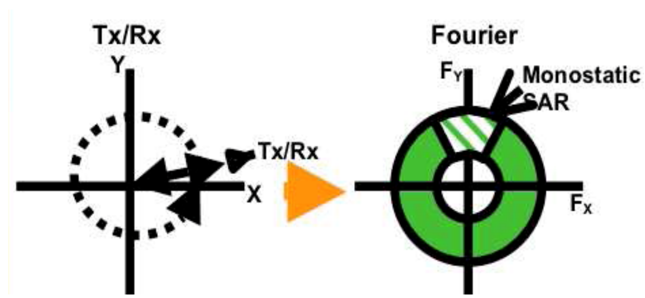
Case 2: Stationary Tx, Moving Rx, UNB waveform



Case 3: Stationary Tx, Moving Rx, Wideband waveform



Case 4: Monostatic Tx/Rx, Wideband waveform

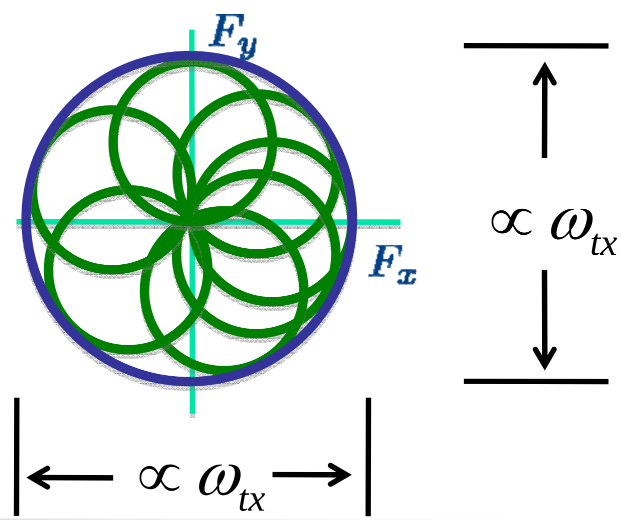


Karl

Example: UNB Multistatic SAR

- UNB (single frequency)
- N_{tx}=10, N_{rx} = 55 Sparse coverage
- Uniform circular coverage
- Fourier support (resolution) $\propto$ UNB frequency

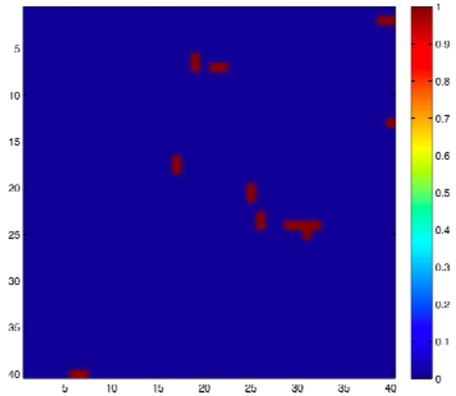
$$\boxed{\hat{f} = \arg\min_{f} \| y - Hf \|_2^2 + \lambda \| f \|_1^1}$$



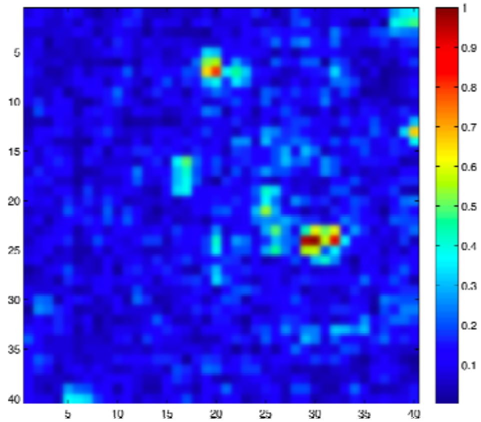
Example: UNB Multistatic SAR

Karl

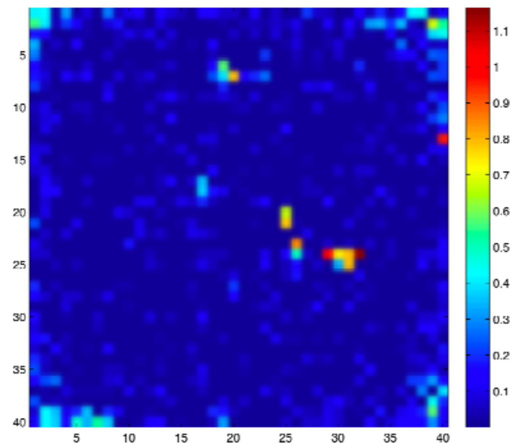
Truth



FBP, cw = 2MHz, SNR = 15dB



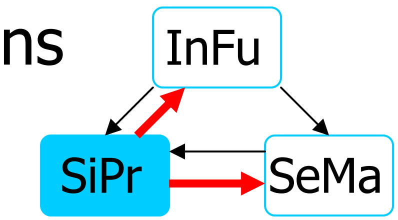
LS-L1, cw = 2MHz, SNR = 15dB



Understanding Performance

Karl

- Predict performance of sensor configurations
  - Guidance for sensor management



- Compressed sensing theory: performance bounds from Restricted Isometry constant
  - Use *mutual coherence* of H as tractable surrogate
  - # of measurements needed to reconstruct sparse scene is proportional to (mutual coherence)^2

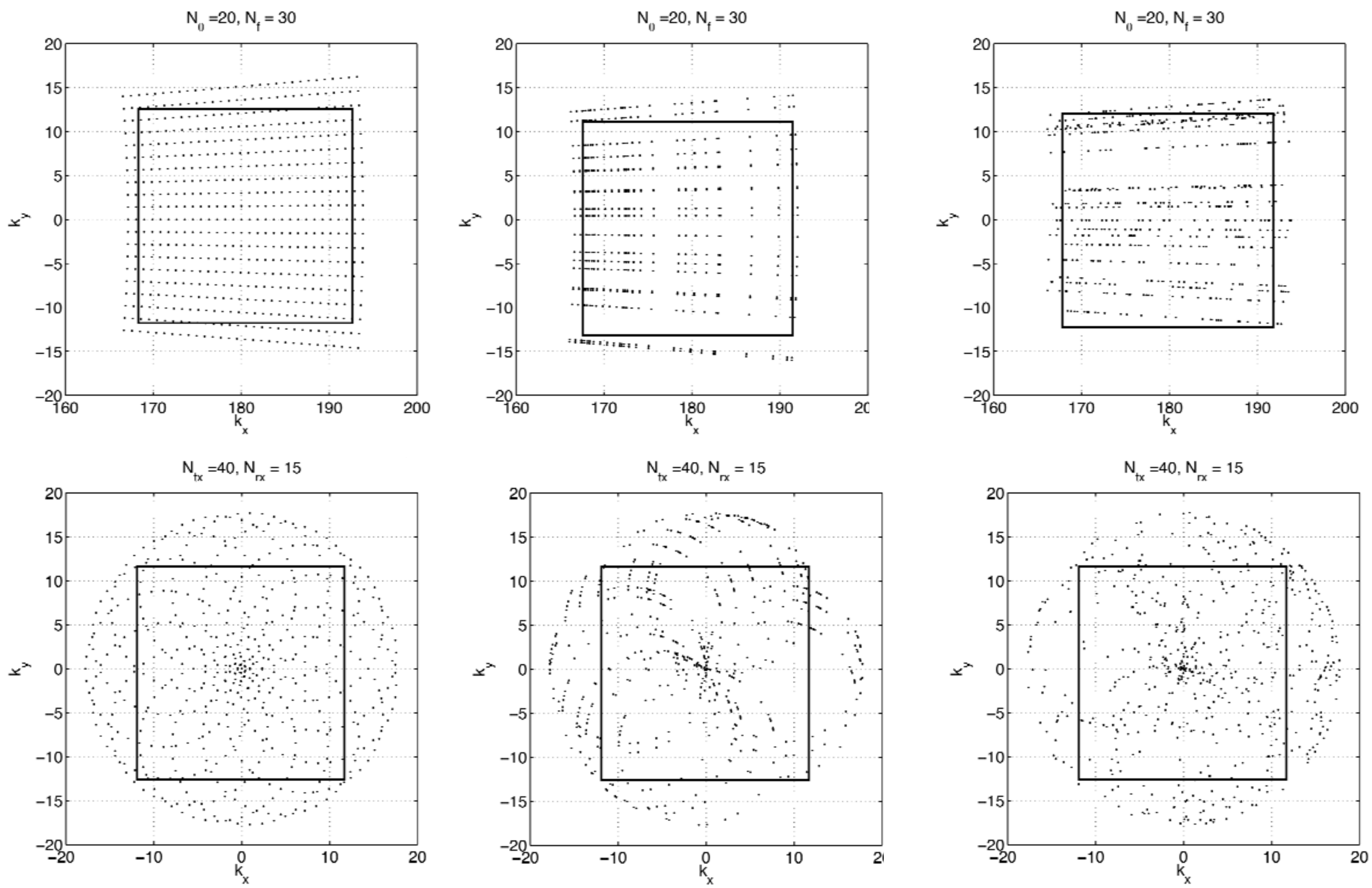
$$\mu[H] = \max \frac{h_i^T h_j}{\| h_i \| \| h_j \|}$$

Example Sampling Strategies

Karl

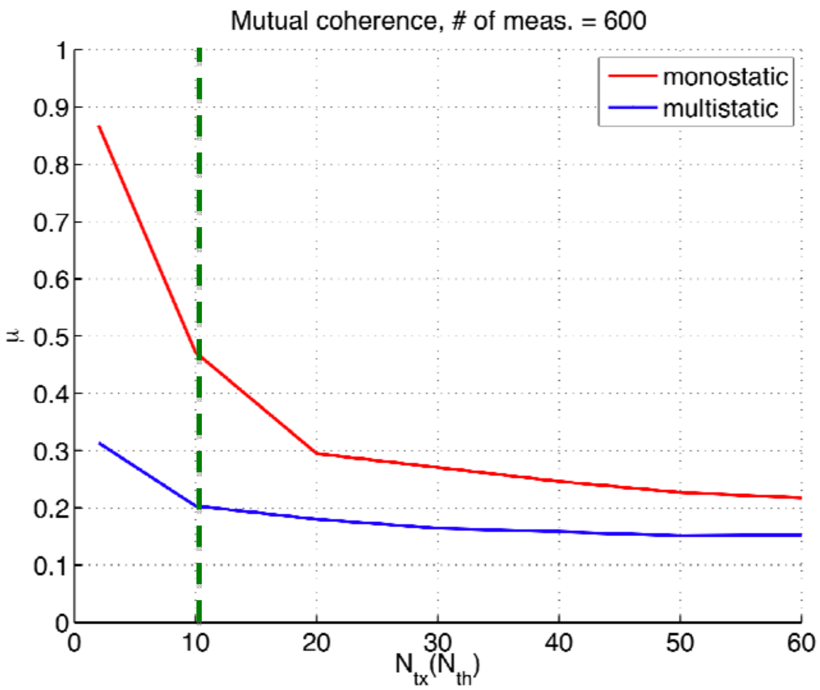
Monostatic

Multistatic



Results: image quality prediction

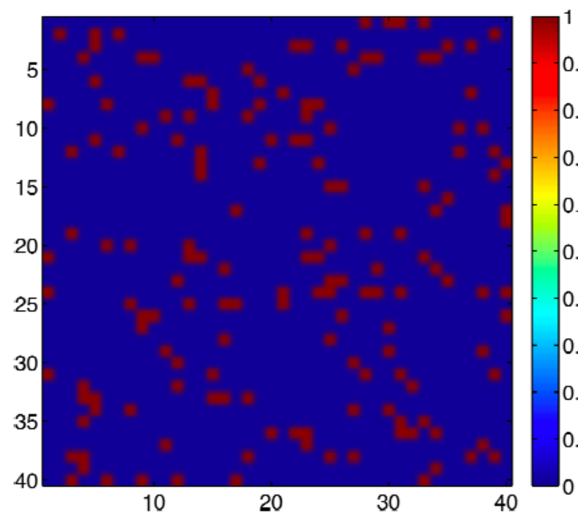
- Mutual coherence lower for multistatic configuration as number of probes are reduced



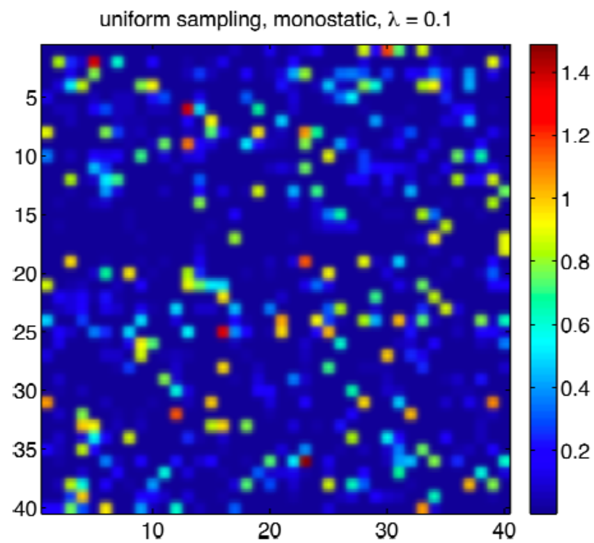
Results, continued

Karl

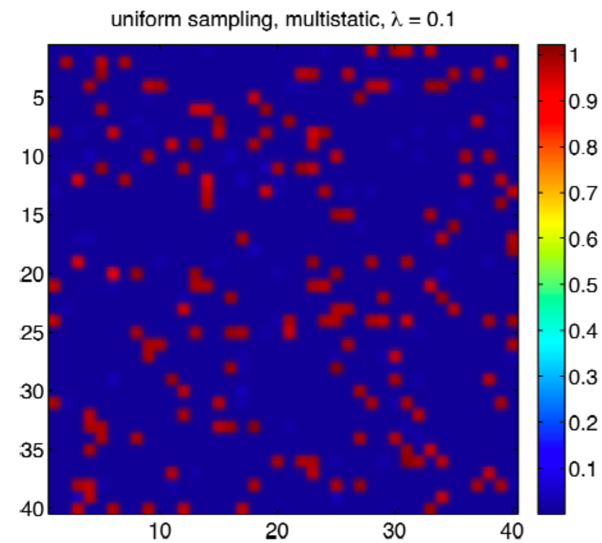
- Example reconstruction for N_{tx}/N_{θ}=10 case
- Reconstructions confirm prediction



Ground Truth



Monostatic



Multistatic

Dynamic Scenes: Moving Targets

Karl

- Augment model to include velocity

$$y_{rx_i,tx_i}(t) = \iint_{|r|\le L} \underbrace{f^{t_{ref}}(r)e^{-jK(t)[(s_{rx_i}-s_{tx_i})\cdot r]}}_{\text{Static targets at a reference time}} \underbrace{e^{j\varphi_{rx_i,tx_i}(v(r))}}_{\text{Phase shift due to motion}} dr$$

- Insight: use sparsest solution to jointly identify correct velocity and scattering:

$$y = \sum_{\text{Pixels } p} A_p(v_p) f_p^{t_{ref}} + n$$

A depends on *unknown* scatterer velocity v in pixel p, so nonlinear problem!

Overcomplete Problem Solution

Karl

- Linearize by sampling velocity

$$\hat{\mathbf{f}} = \arg\min_{\mathbf{f}_b} \| y - \mathbf{A}(\widetilde{V})\mathbf{f} \| + \lambda \| \mathbf{f} \|_1^1$$

$$\hat{f}_p^{\,t_{ref}} = \max_{\tilde{v}_p} \hat{\mathbf{f}}_p$$

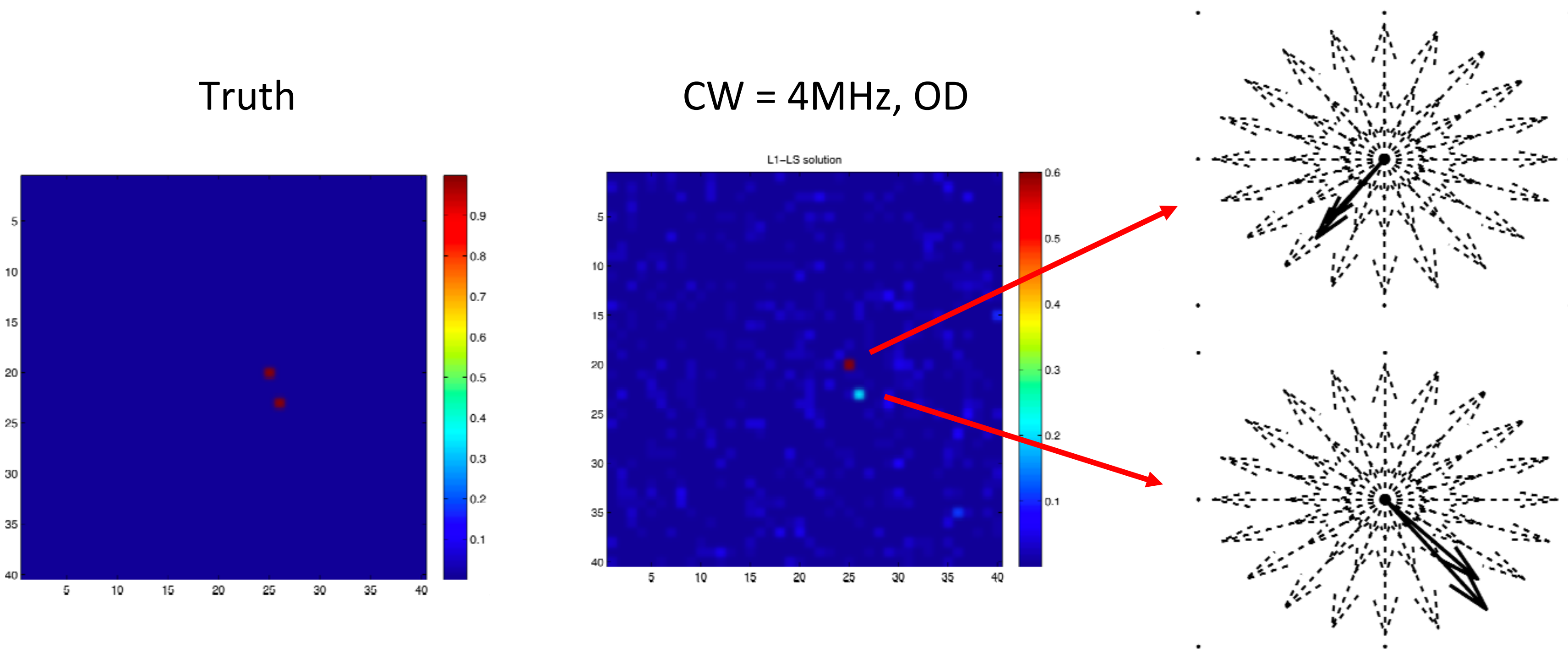
Karl

Example: Multistatic MT imaging

- Multistatic configuration with Ntx= 10, Nrx = 55
- Dictionary does not contain true velocities

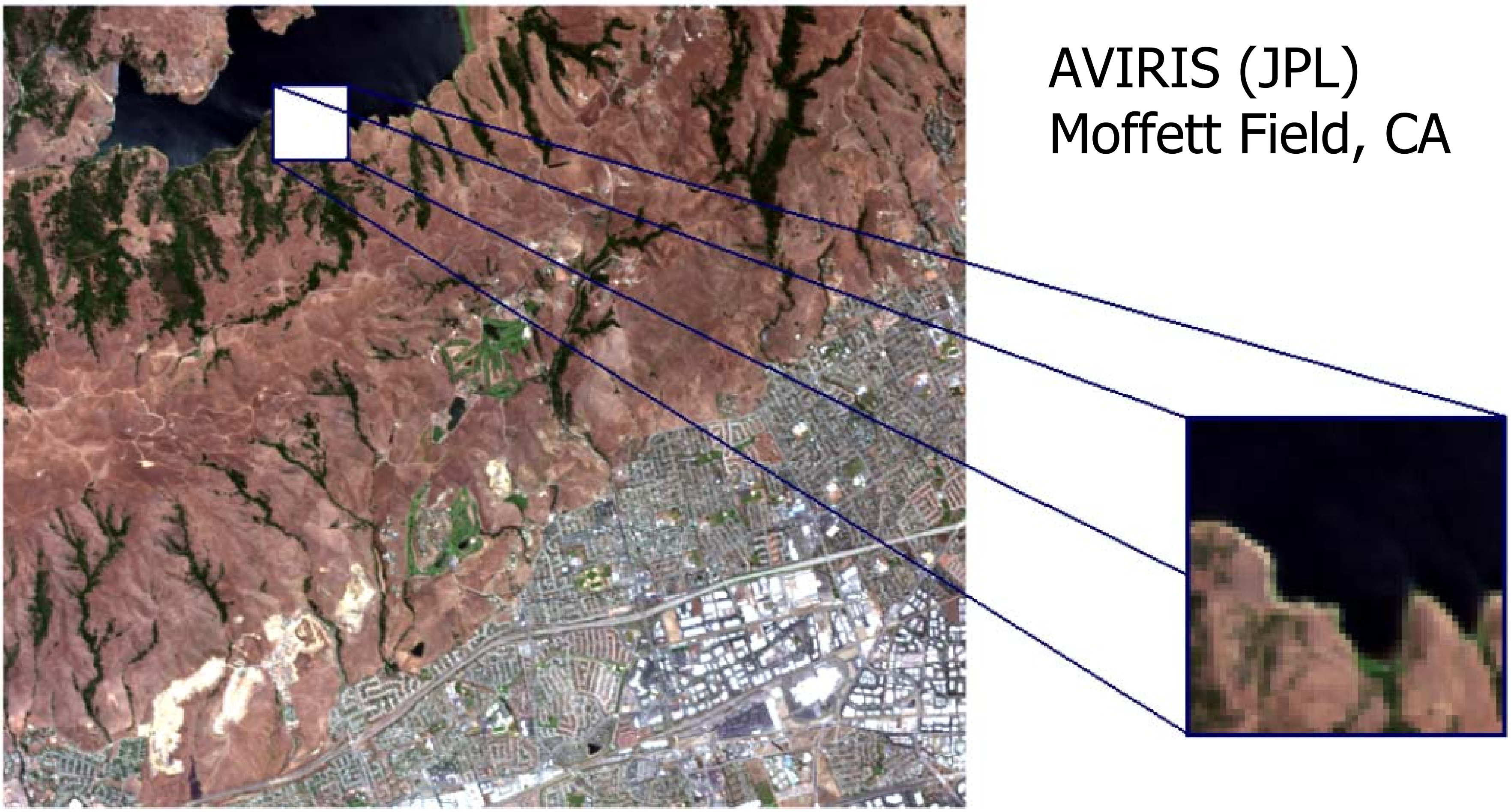
Truth

CW = 4MHz, OD



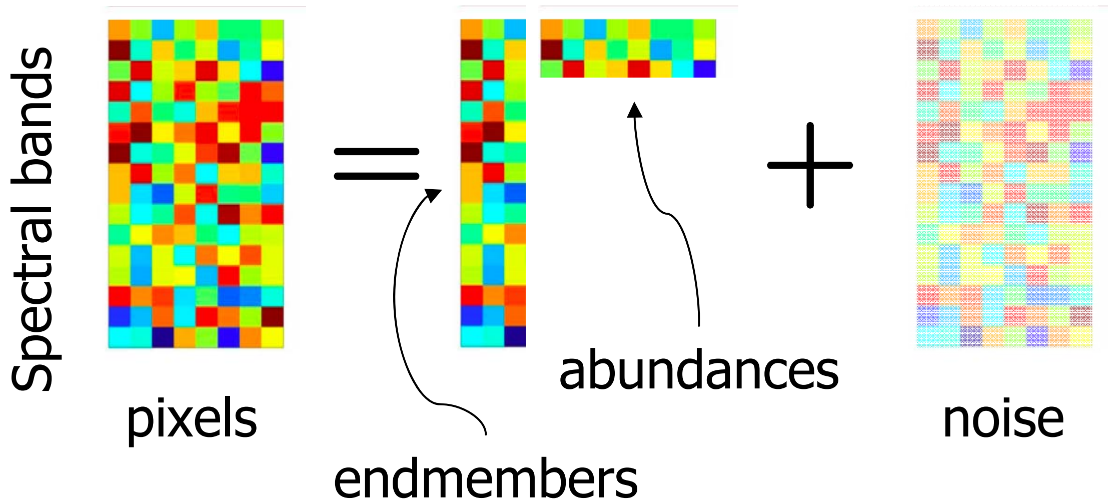
Hyperspectral image

Hero



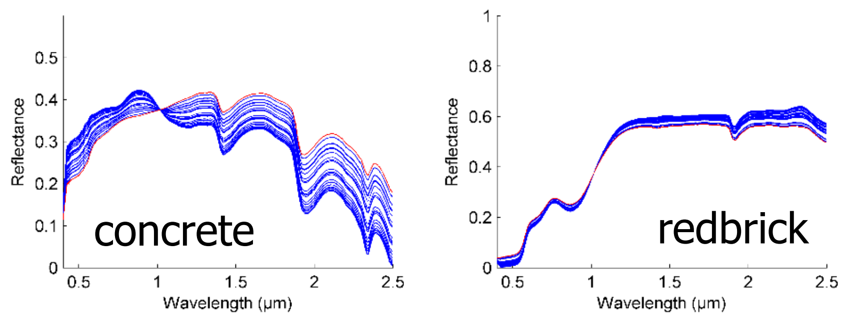
AVIRIS (JPL)
Moffett Field, CA

Hyperspectral Unmixing



Abundances:
- Nonnegative
- Columns sum to 1

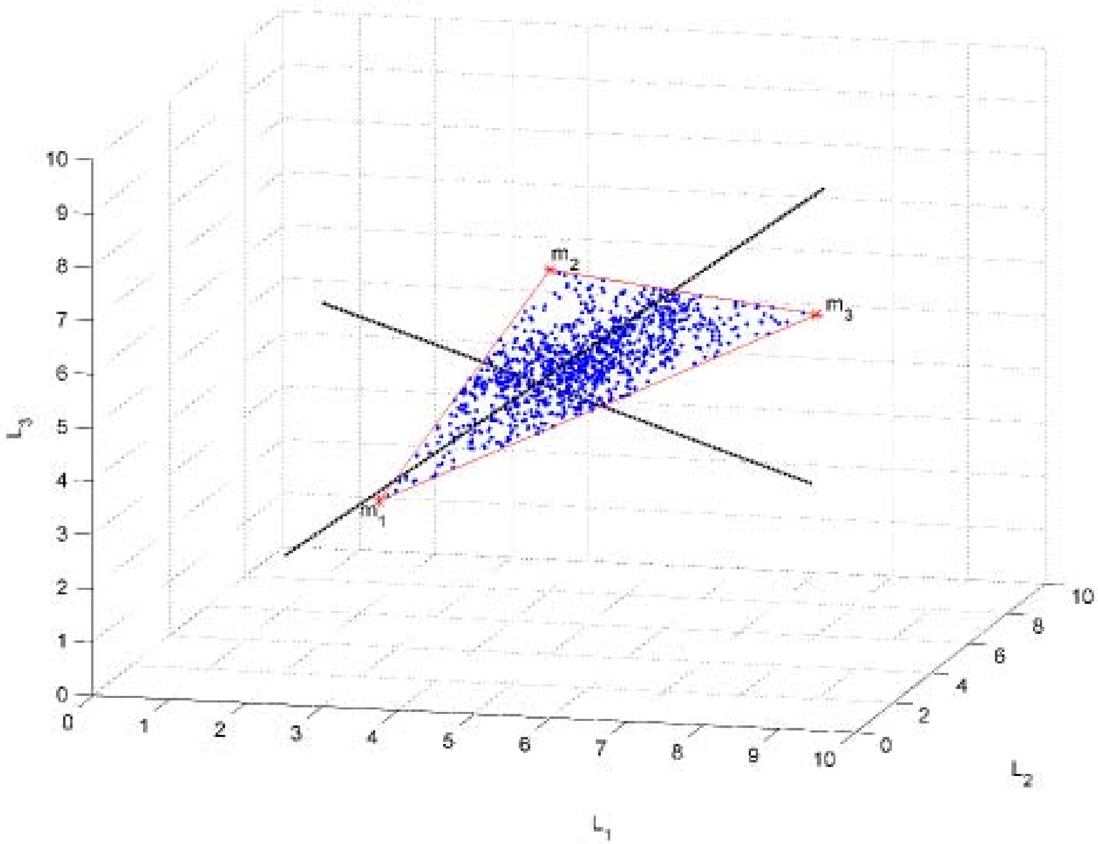
Endmembers:
- Nonnegative



[graphic adapted from R. Baraniuk]

Dimension reduction

- Mixing coefficients lie on R-1 dimensional simplex



<u>Thus, exploit parsimony</u>

Represent signals in the subspace identified by PCA (eigendecomposition of the data covariance matrix)

Hierarchical Bayesian model

Hero

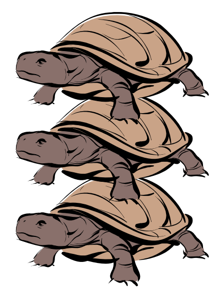
- Graphical model structure induces posterior

$$f\left(\mathbf{C}, \mathbf{T}, \boldsymbol{\sigma}^2 \middle| \mathbf{Y}\right) \propto \prod_{p=1} \mathbf{1}_{\mathcal{S}}\left(\mathbf{c}_p\right)$$

$$\times \prod_{r=1}^{R} \exp\left[-\frac{\left\|\mathbf{t}_r - \mathbf{e}_r\right\|^2}{2s_r^2}\right] \mathbf{1}_{\mathcal{T}_r}\left(\mathbf{t}_r\right)$$

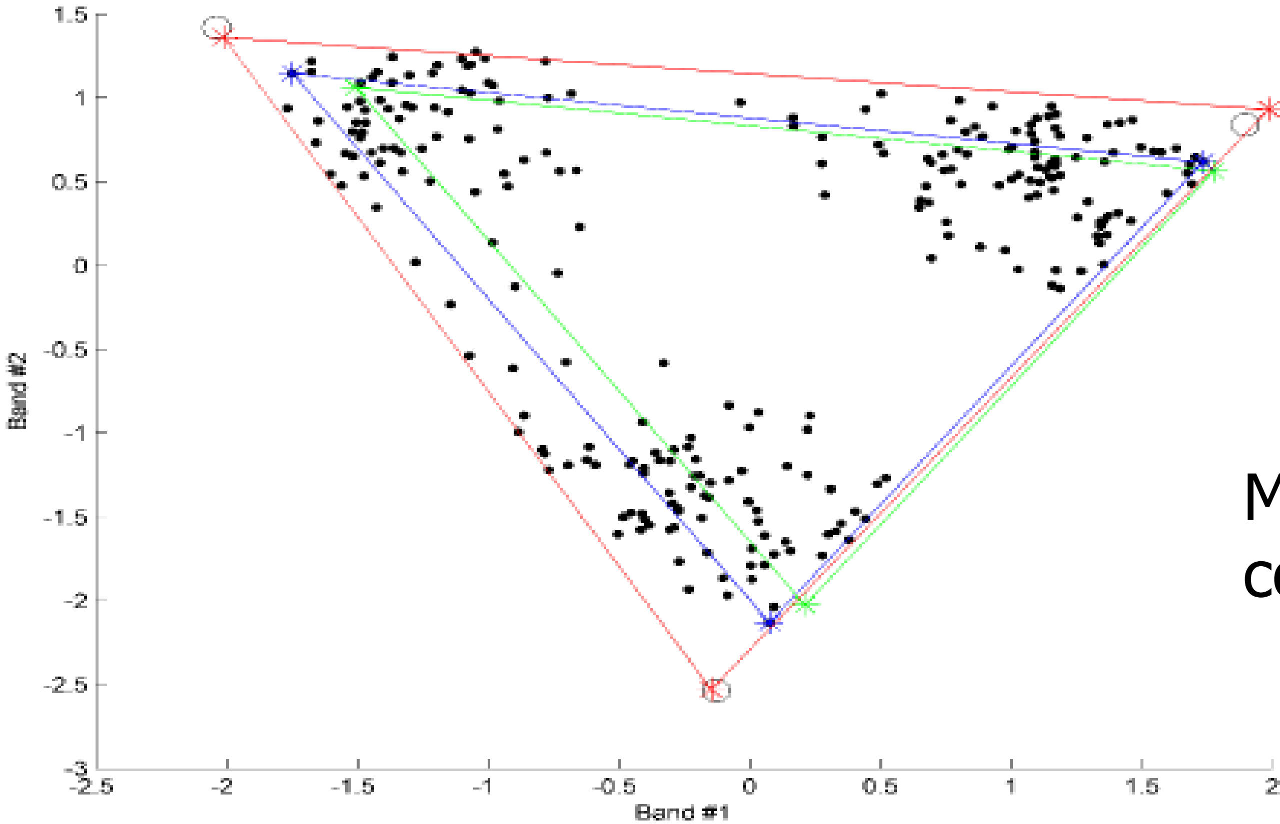
$$\times \prod_{p=1}^{P} \left[\left(\frac{1}{\sigma_p^2}\right)^{\frac{L}{2}+1} \exp\left[-\frac{\left\|\mathbf{y}_p - \left(\mathbf{U}\mathbf{T} + \bar{\mathbf{y}}\right)\mathbf{a}_p\right\|^2}{2\sigma_p^2}\right]\right]$$

- Abundances: uniform prior on simplex
- Endmembers: multivariate Gaussian; invGamma hyperparameters with Jeffries hyperprior



Unmixing results: data projected to simplex

Hero

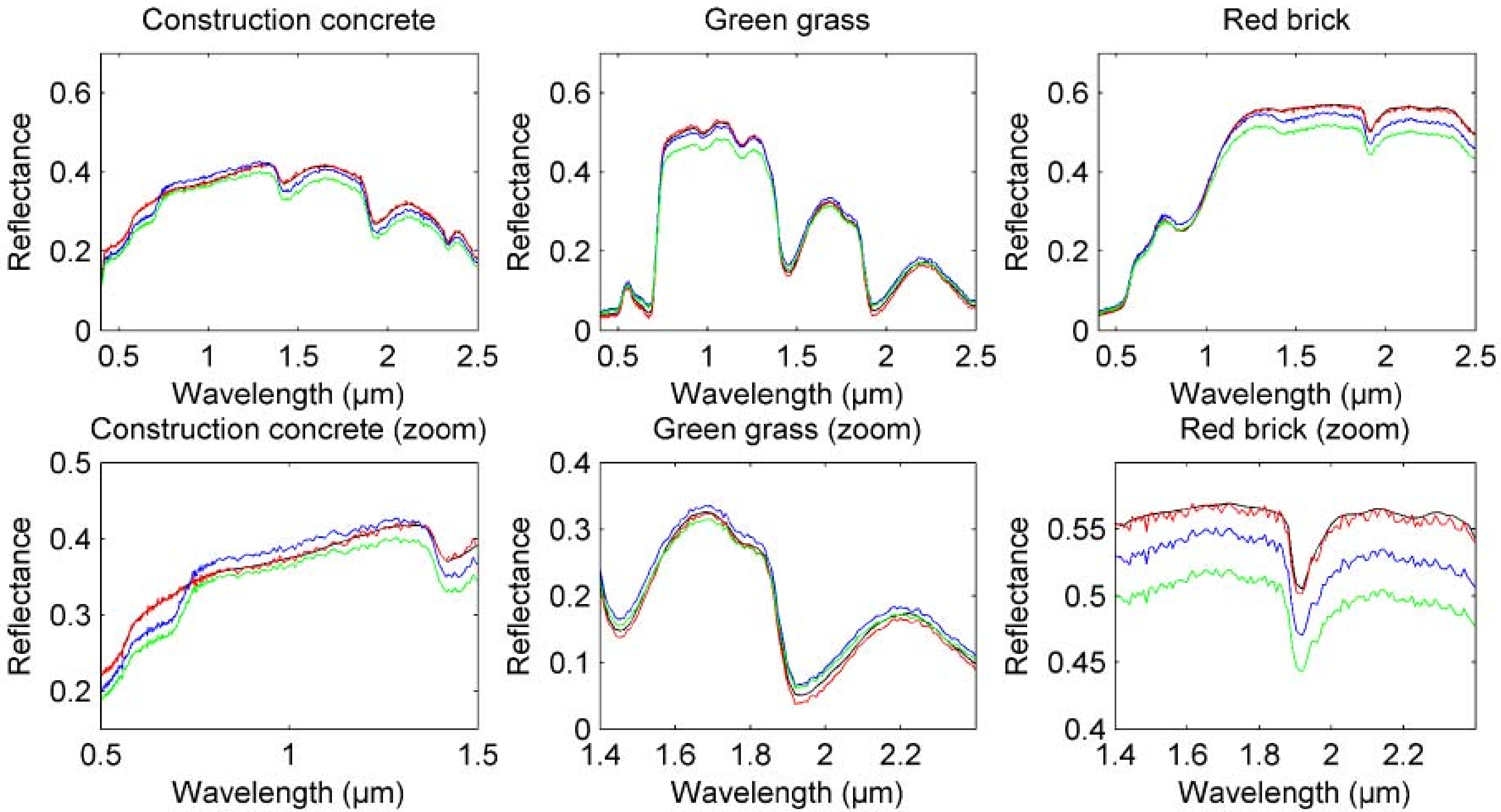


MCMC computation

Fig. 5. Scatter plot in the lower-dimensional space $\mathcal{V}_2$: projected dataset (black points), actual endmembers (black circles), endmembers estimated by N-FINDR (blue stars), endmembers estimated by VCA (green stars) and endmembers estimated by proposed approach (red stars).

Unmixing results: endmembers

Hero



AVIRIS Data Moffett Field, CA

Endmember estimates

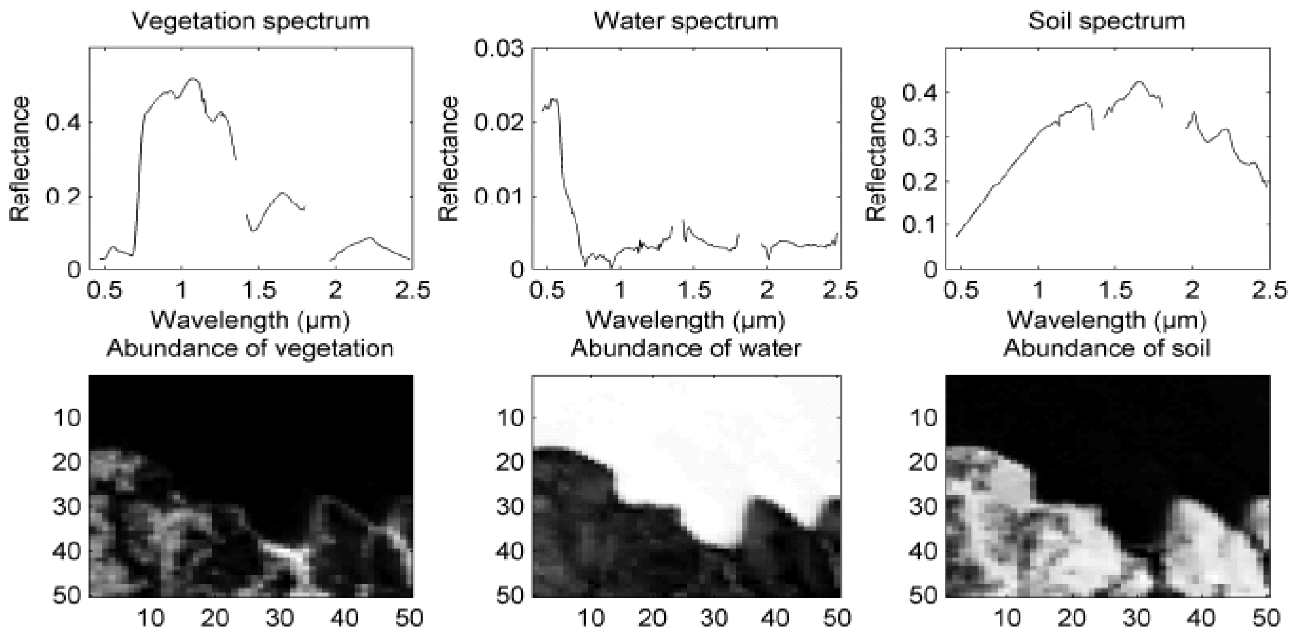


Image segmentation

189 spectral bands (after deletion of water absorption bands)

Hyperspectral unmixing: summary

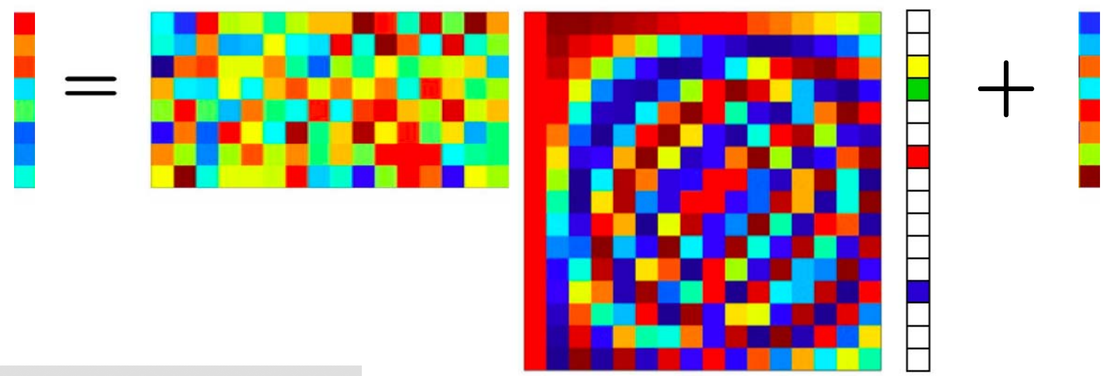
Hero

- Jointly estimate endmembers and abundances using a unified graphical model
  - Combines hierarchical graphical models and dimension reduction
  - significantly improves performance wrt state-of-the-art (N-FINDR, VCR)
- Yield MMSE solution by averaging over likely solutions
  - Report posterior confidence

Sparse Linear Regression

Potter

$$y = \Phi x + e$$



"Are you guys still working on As + n ?"

Thomas Kailath, c. 1988

"The thing that hath been, it is that which shall be; and that which is done is that which shall be done: and there is no new thing under the sun."

Ecclesiastes 1:9, c. BC 250

"There is nothing new under the sun but there are lots of old things we don't know."

Ambrose Bierce, *The Devil's Dictionary*, *US author & satirist (1842 - 1914)*

"Neurosis is the inability to tolerate ambiguity."

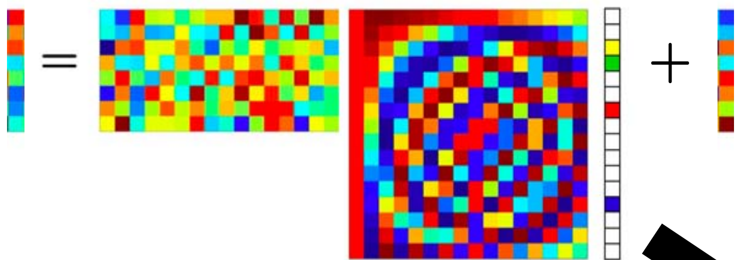
Sigmund Freud (1856 – 1939)

[graphic adapted from R. Baraniuk]

Detection and Estimation Goals

Potter

$$y = \Phi x + e$$



$x \in \mathbb{R}^N$

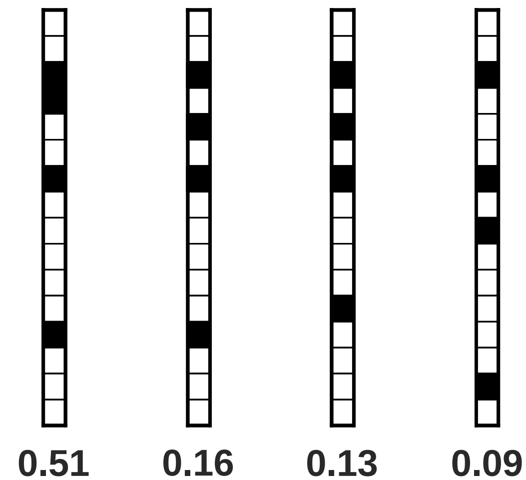
$\Phi : \mathbb{R}^N \mapsto \mathbb{R}^M$

$N =$ number of unknowns

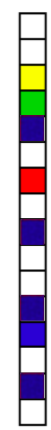
$M =$ number of measurements

$M < N$

- Soft-decision detection



- MMSE estimation



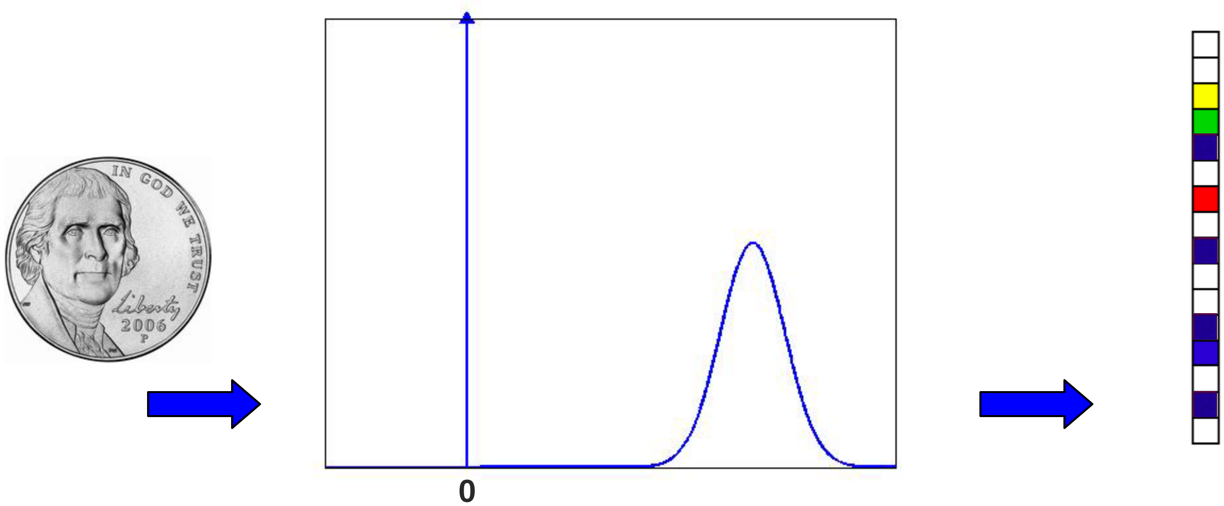
Desiderata

- Report ambiguity
  - Compute posterior densities for variable sets & values
  - Allow arbitrary correlation among columns of Φ
- Minimize mean square estimation error
  - MMSE estimate of variables
- Use domain knowledge, if available
  - Interpretable family of priors with known hyperparameters, or
  - ML estimation of hyper-parameters
- Compute with low complexity
  - Keep order of complexity of Orthogonal Matched Pursuits
- Admit complex-valued data
  - Band-pass signals in radar, spectroscopy and communications

In a Nutshell…

Potter

- Bayesian model: Gaussian mixture
- Effective tree search for high-probability set
- Fast update of posterior
- Generalized EM for unknown hyperparameters



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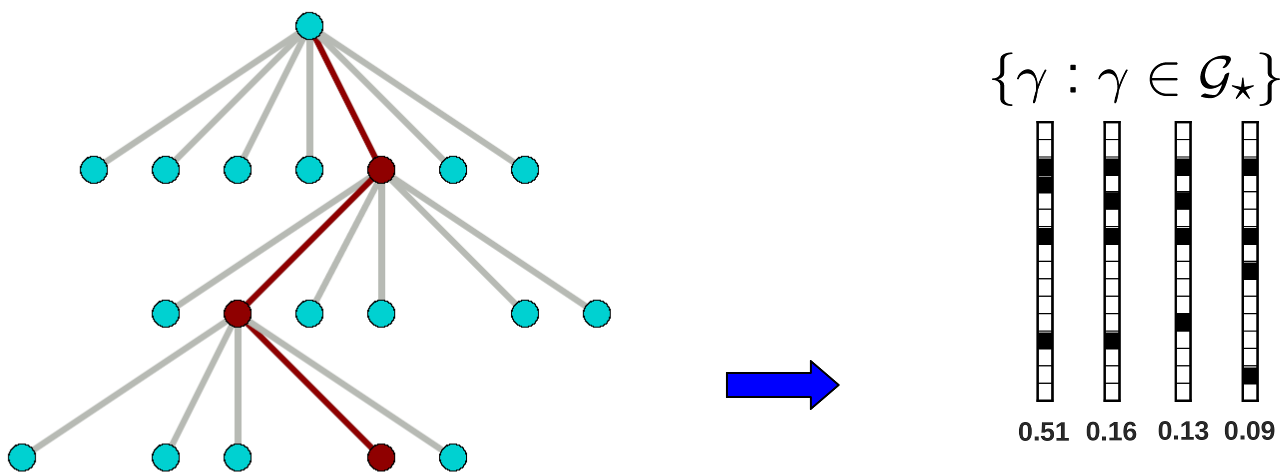

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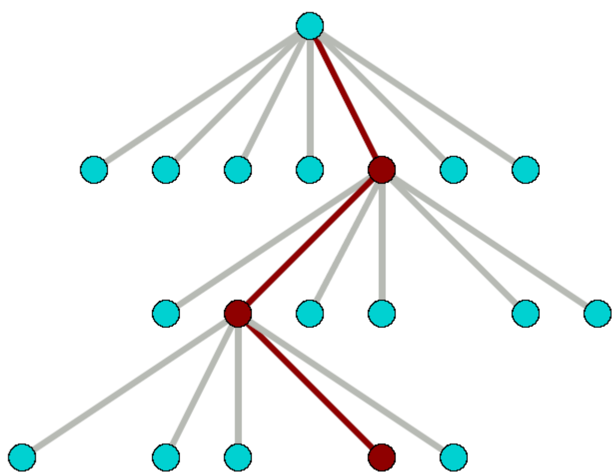

$$\Delta_{n,q'}(\boldsymbol{s},\boldsymbol{y}) := \nu(\boldsymbol{s}',\boldsymbol{y}) - \nu(\boldsymbol{s},\boldsymbol{y})$$

Exponential search, $O(2^N)$ becomes linear O(NMK)

In a Nutshell…

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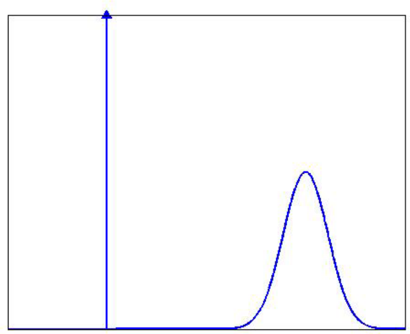
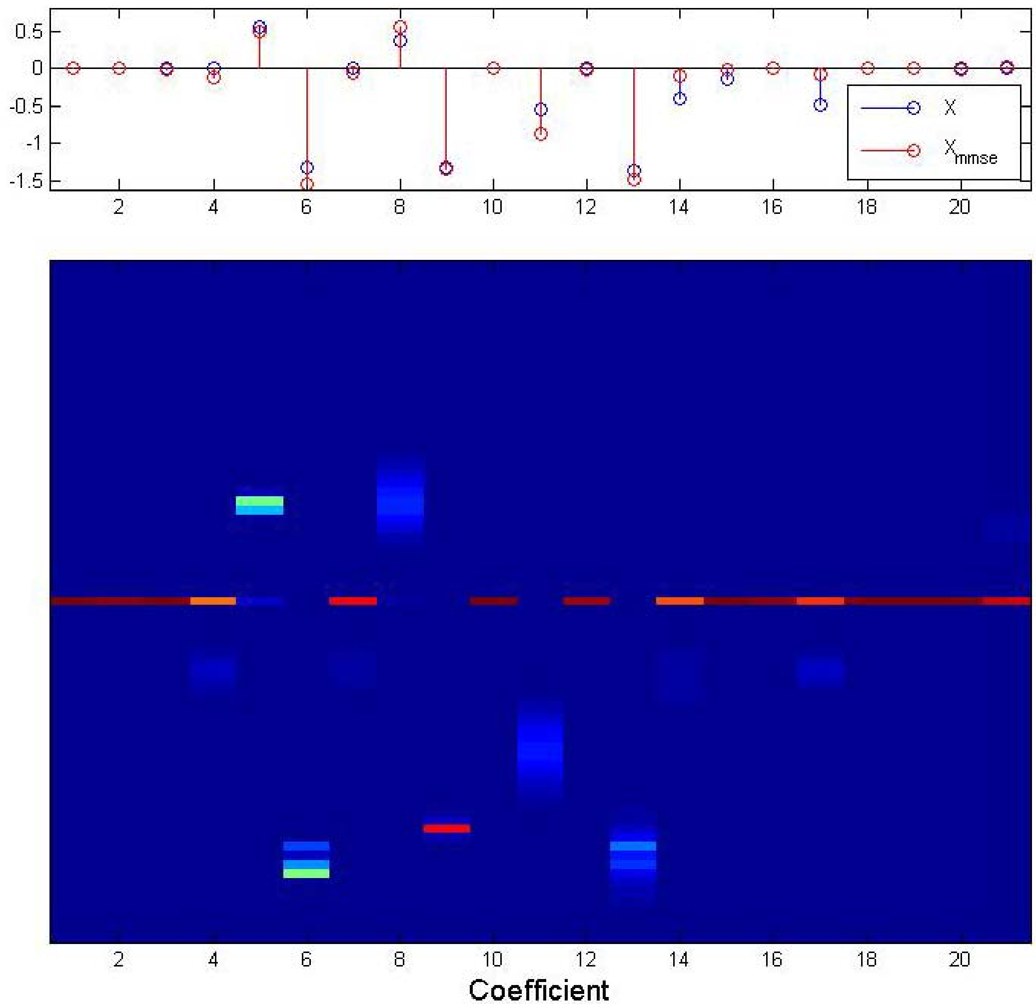
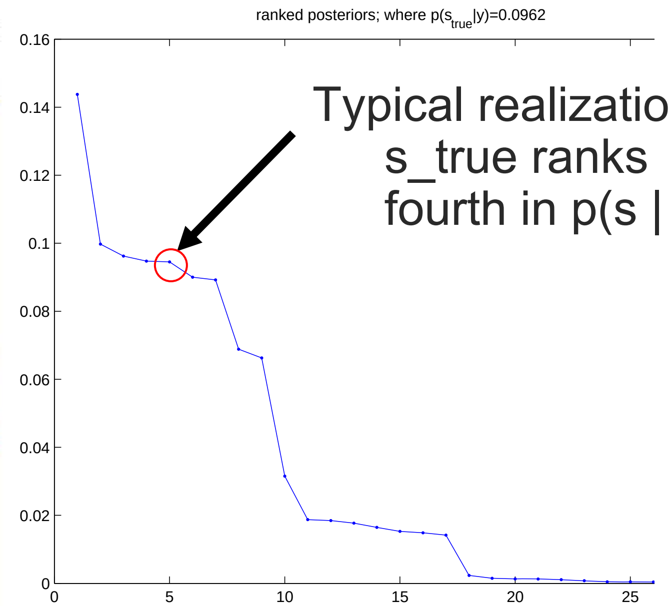


Learn hyperparameters from data.
ML estimate "empirical Bayes."

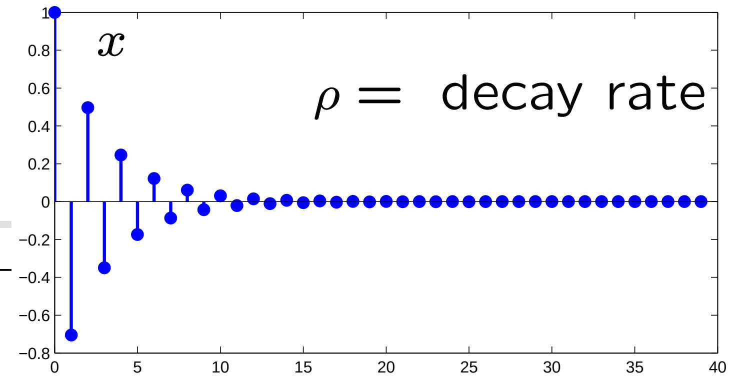
Posterior, p(x|y)



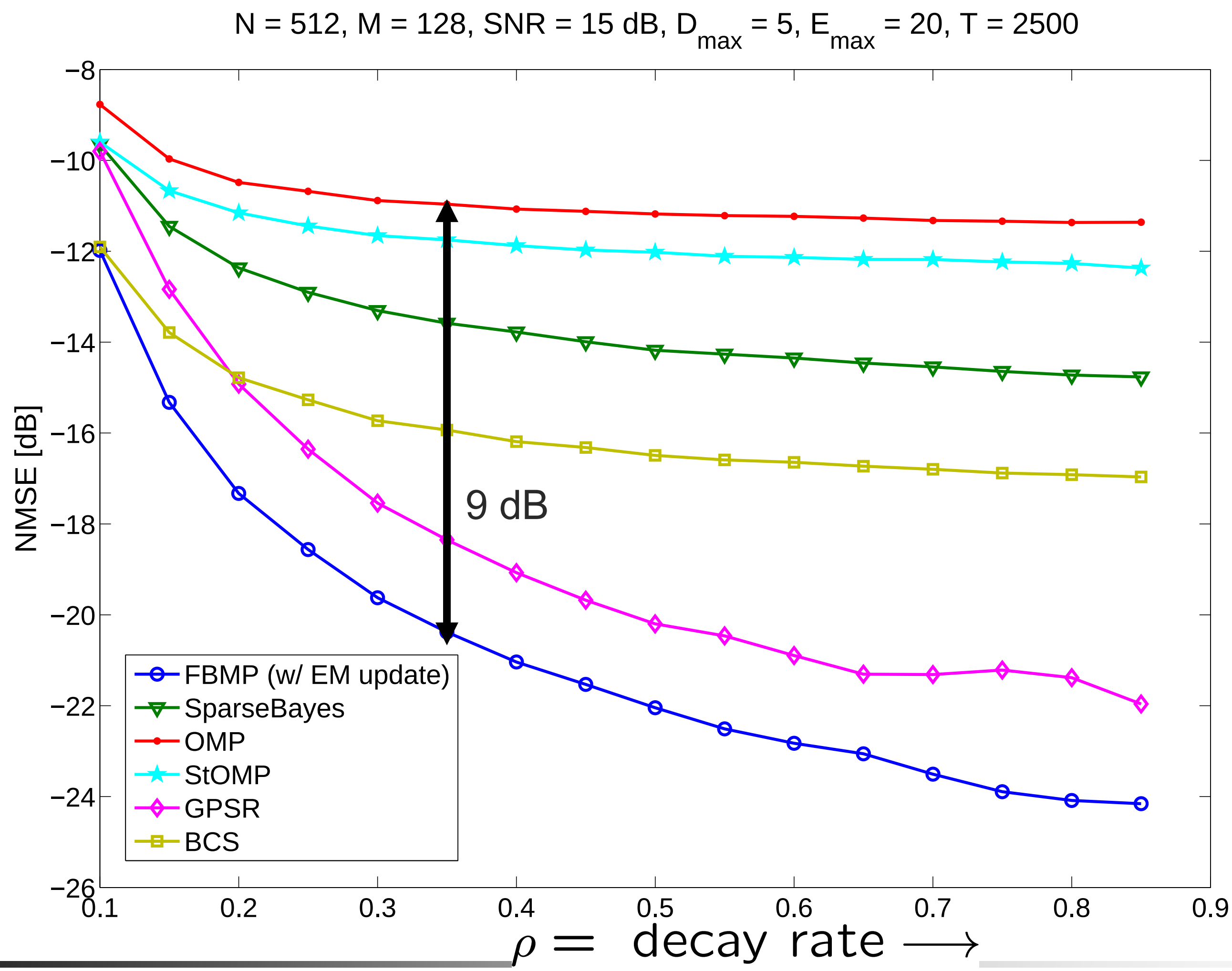


Typical realization:
s_true ranks
fourth in p(s | y)

Numerical Experiments

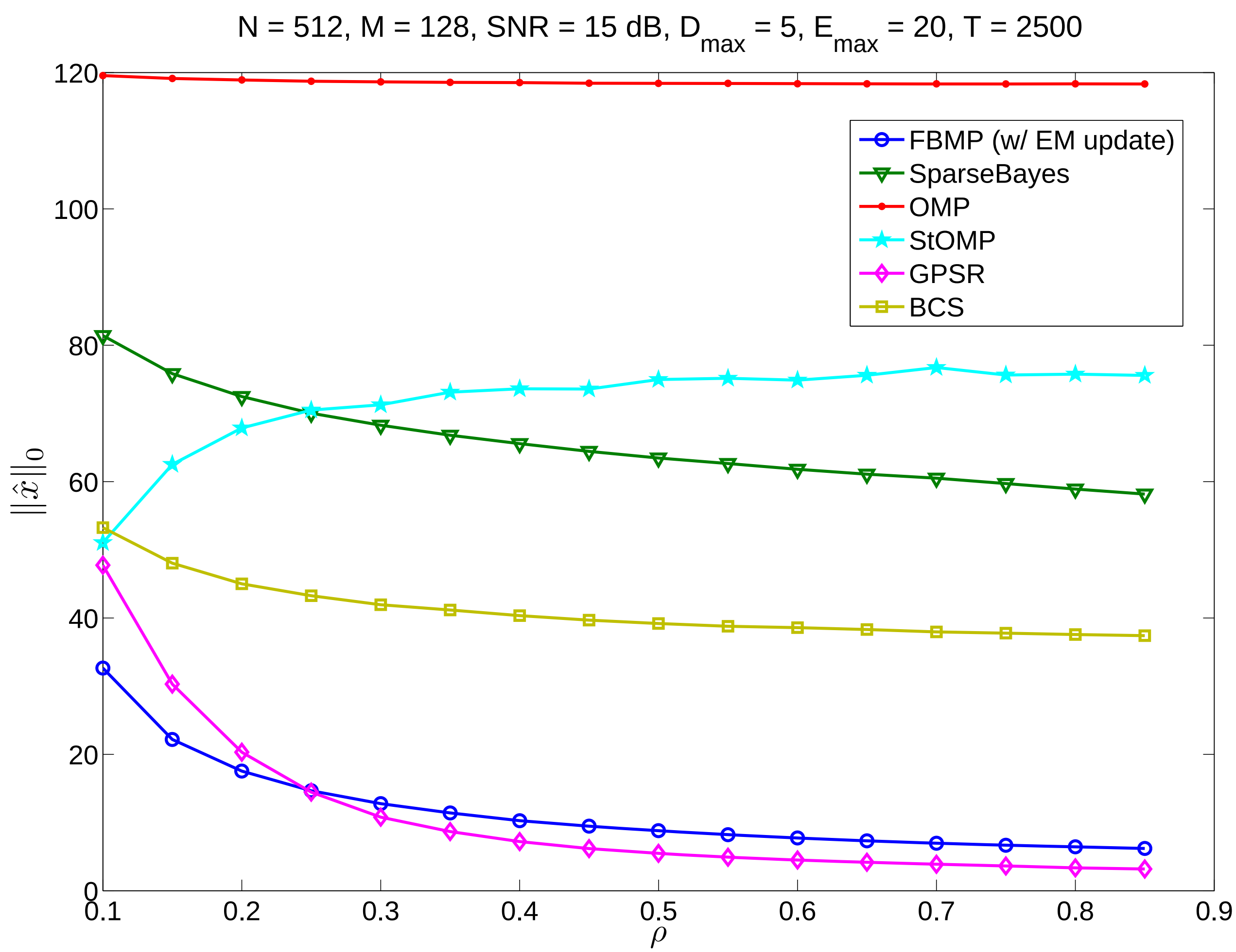


NMSE



N = 512, M = 128, SNR = 15 dB, D max = 5, E max = 20, T = 2500
NMSE [dB]
−8
−10
−12
−14
−16
−18
−20
−22
−24
−26
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
9 dB
FBMP (w/ EM update)
SparseBayes
OMP
StOMP
GPSR
BCS
ρ = decay rate ⟶

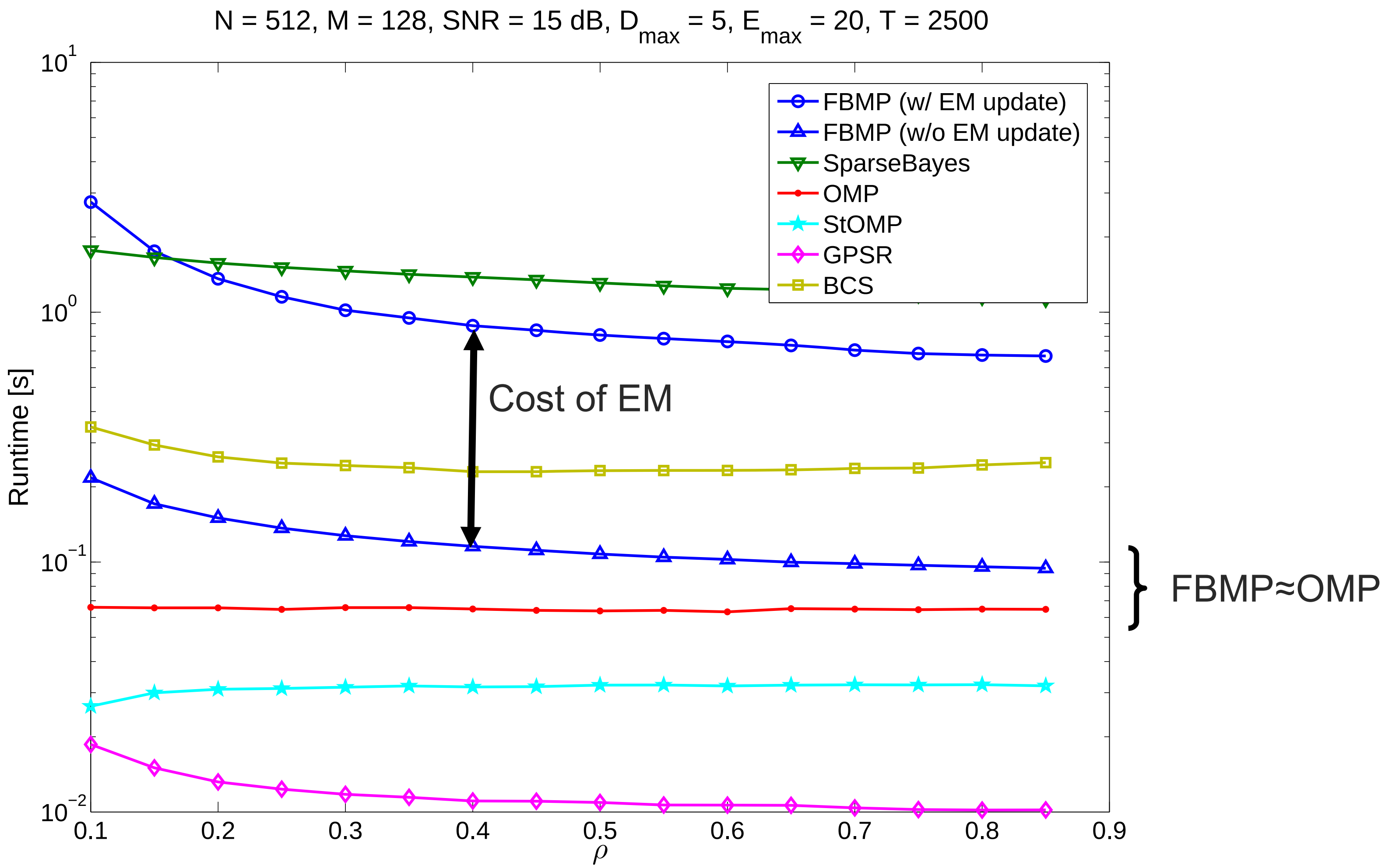
Sparsity



N = 512, M = 128, SNR = 15 dB, D max = 5, E max = 20, T = 2500
FBMP (w/ EM update)
SparseBayes
OMP
StOMP
GPSR
BCS
120
100
80
60
40
20
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
ρ
$\|\hat{x}\|_0$

Runtime

Potter



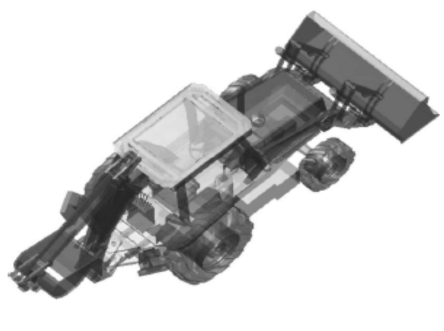
Hyperparameter Selection

Cetin

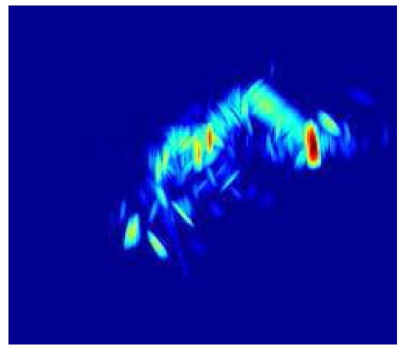
- Sparsity-based L2-Lp reconstruction

$$\hat{f} = \arg\min_{f} \| y - Hf \|_2^2 + \lambda \| f \|_p^p$$

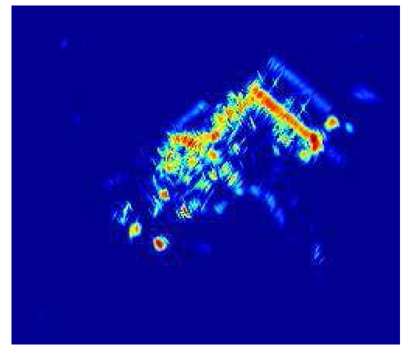
backhoe model



conventional image



sparsity-based image



- … but requires the selection of the hyper-parameter λ
- Goal: Automatic choice of hyper-parameter

Approaches and Numerical Methods

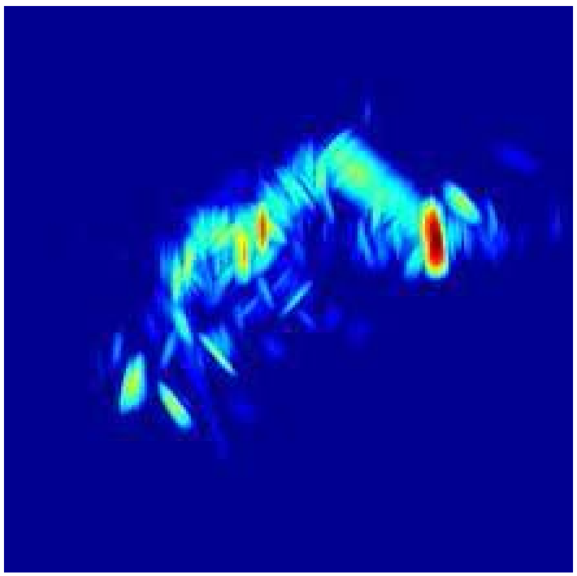
Cetin

- Adaptation of the following parameter choice methods for sparsity-driven SAR imaging:
  - Stein's unbiased risk estimator (SURE)
  - Generalized cross-validation (GCV)
  - L-curve
- Numerical tools for efficient implementation of these methods, including
  - Randomized trace estimation
  - Derivative-free optimization through Golden section search
  - Numerical derivative computation and backtracking line search

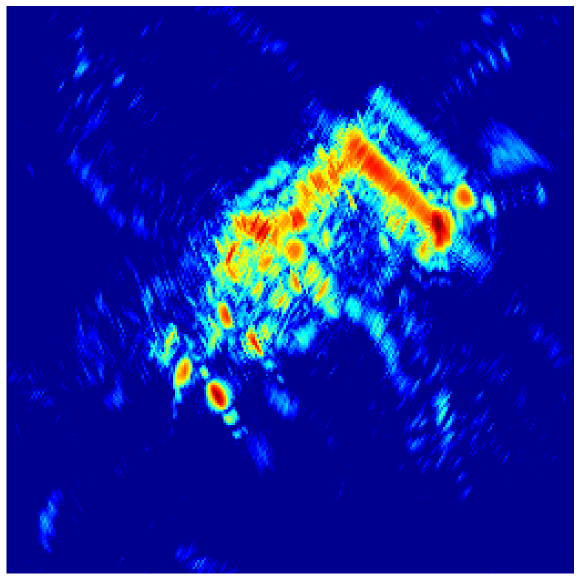
Results: Backhoe, 500 MHz bandwidth

Cetin

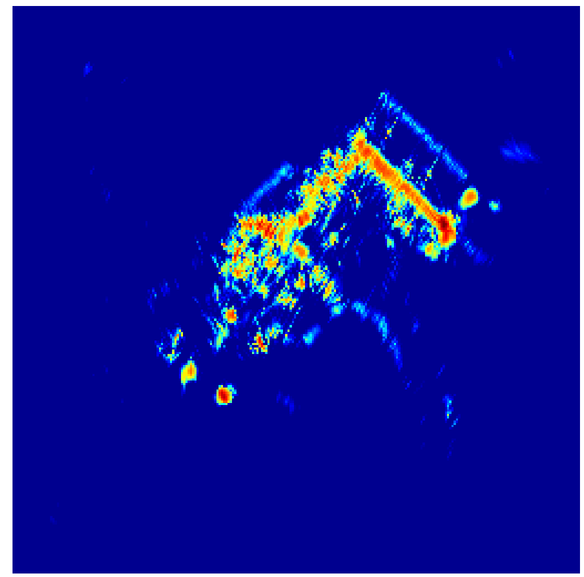
Conventional



GCV≈SURE



L-curve



Learn model parameters from data:
balance models with measurements

Joint imaging and model correction

Cetin

- SAR observation model may not be known perfectly, due to e.g. uncertainties in platform location
- This leads to phase errors in observed data
- We have extended our sparsity-based imaging framework to optimize over the reflectivities and model parameters simultaneously:

$$(\hat{f},\hat{\phi}) = \arg\min_{f,\phi} \| y - H(\phi) f \|_2^2 + \lambda \| f \|_p^p$$

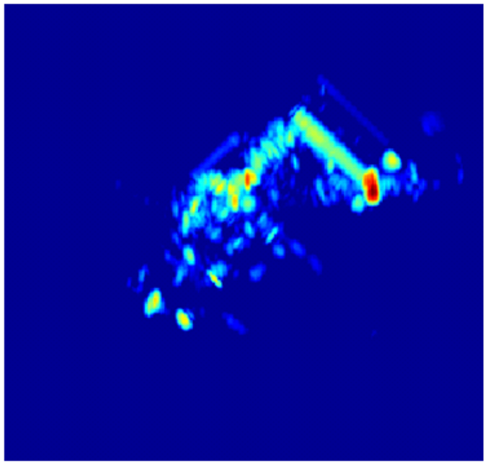
model parameters

Results: Backhoe Data Set

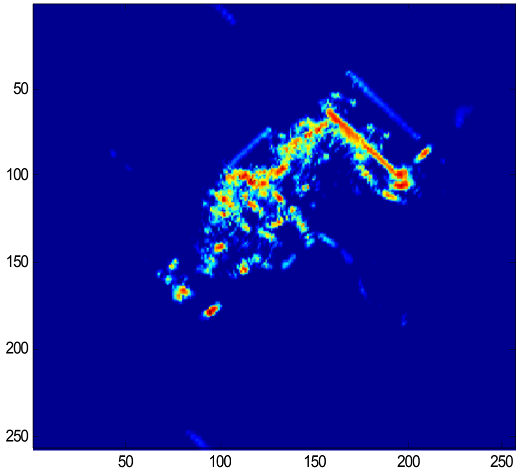
Cetin

Without Model Errors

Conventional image



Sparsity-based image

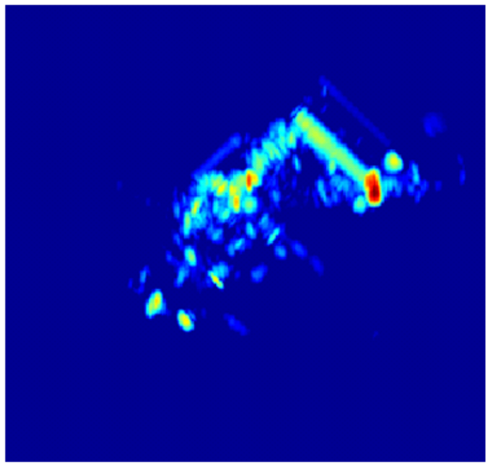


Results: Backhoe Data Set

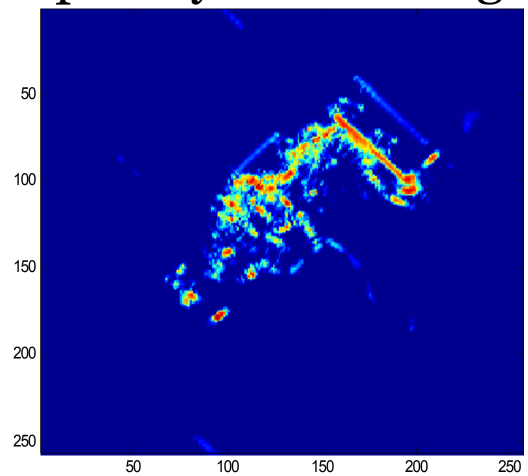
Cetin

Without Model Errors

Conventional image

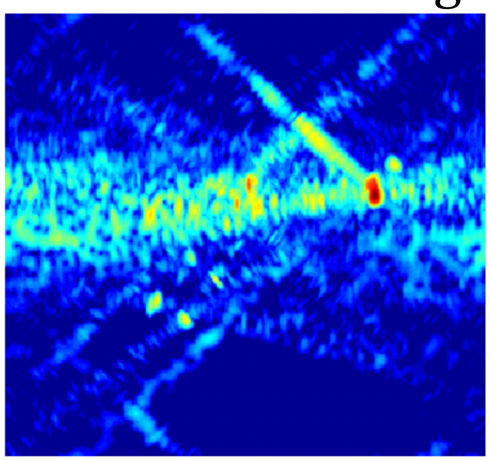


Sparsity-based image

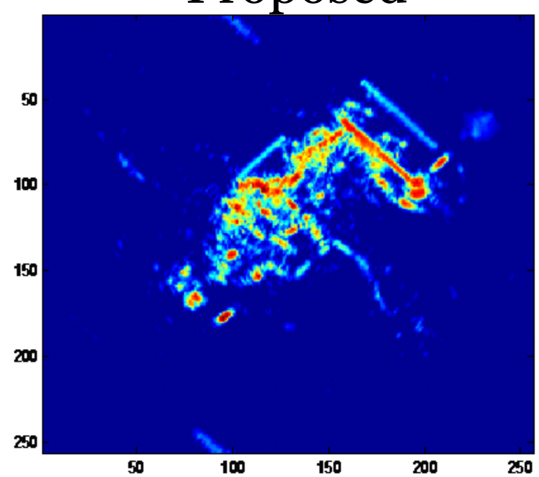


With Model Errors

Conventional image



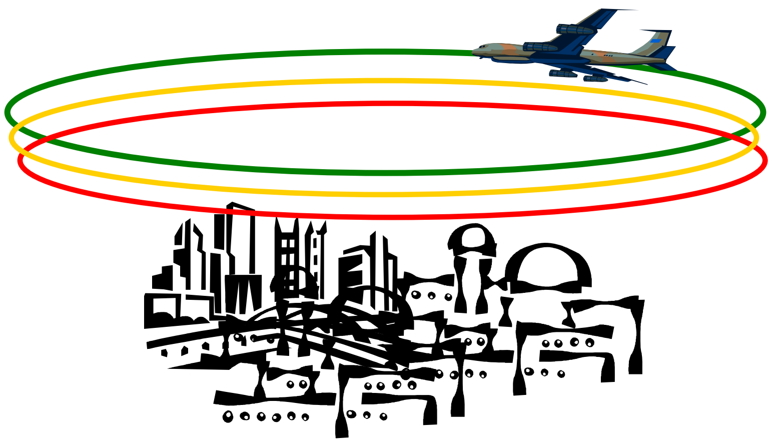
Proposed

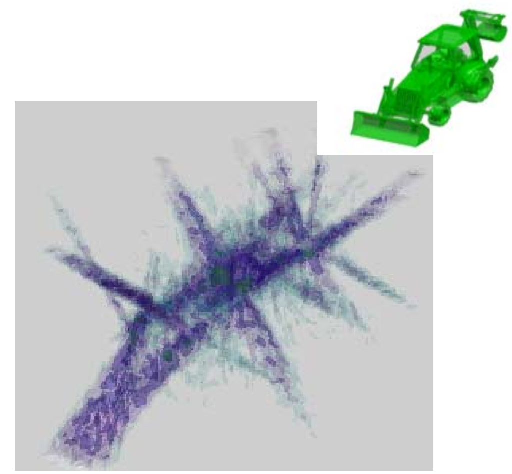


Sparsity-based image with model error correction

Circular SAR

Ertin



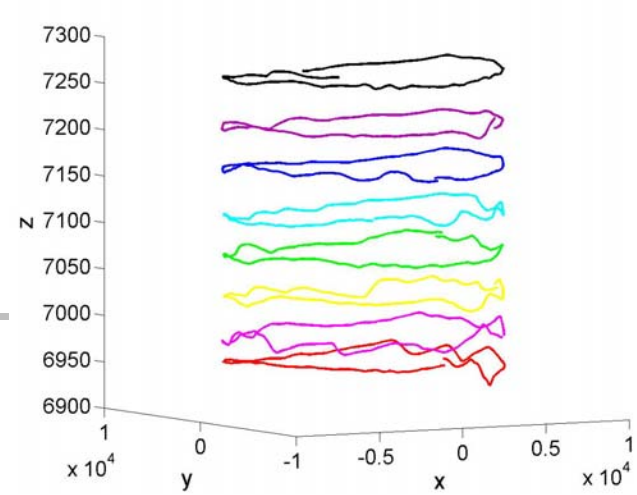


- 3D Imaging by Circular SAR is constrained by
  - Limited Persistence of Reflectors: anisotropy
  - Sparse Elevation Sampling
  - Dynamically varying nonuniform spacing in elevation

3D from circular multipass SAR

Ertin

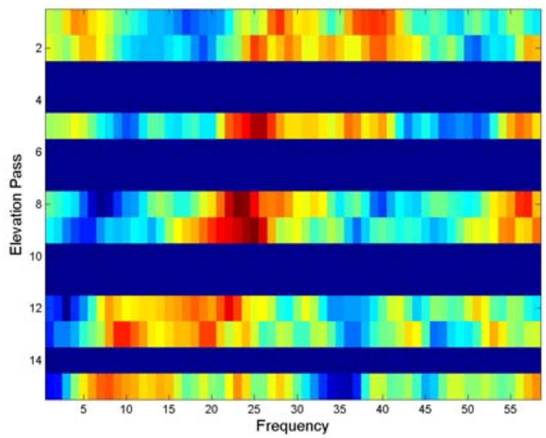
- Sparse Elevation Sampling
  - ESPRIT based parametric interferometric phase estimation
- Limited Persistence of Reflectors
  - Subaperture imaging matched to reflector persistence
- Time-varying nonuniform spacing in elevation
  - Interpolation through sparsity regularized enhancement of single pulse images

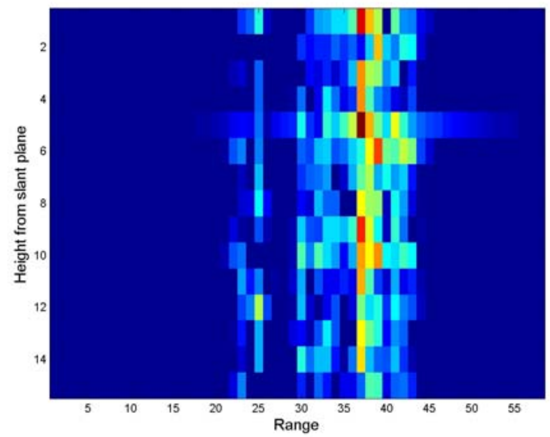


Nonuniform Elevation Sampling

Ertin

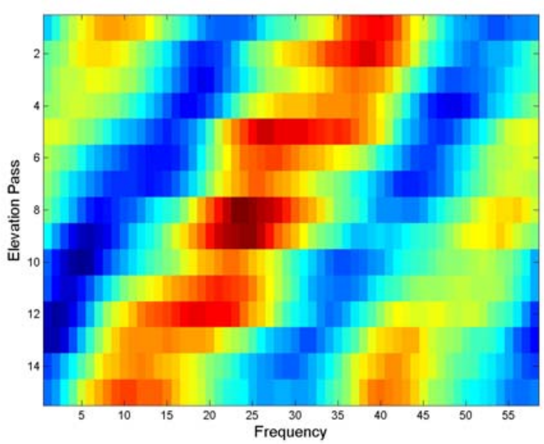
- Interpolation: sparsity regularized single pulse images

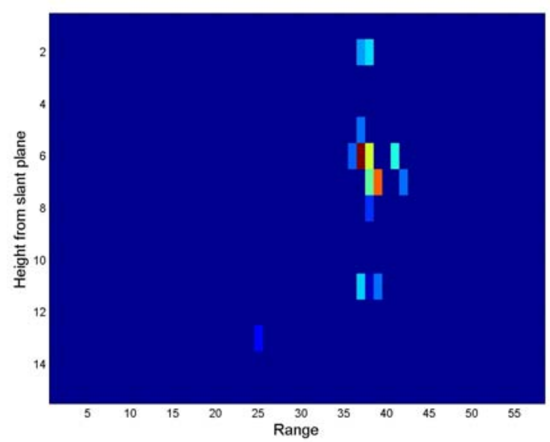




range-height image

$$\arg\min_{x}\{\|H * x - y\|^2 + \lambda\|x\|^p\}$$

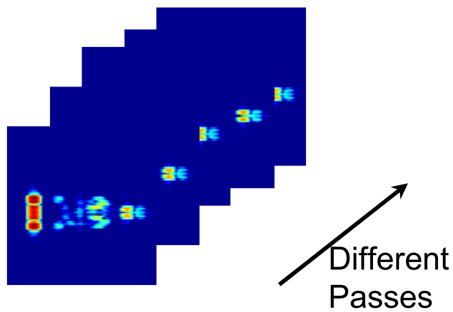


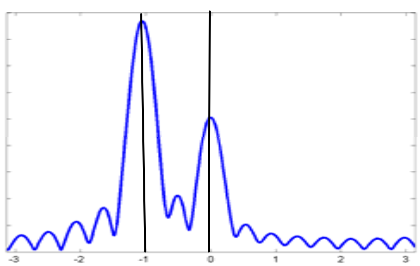


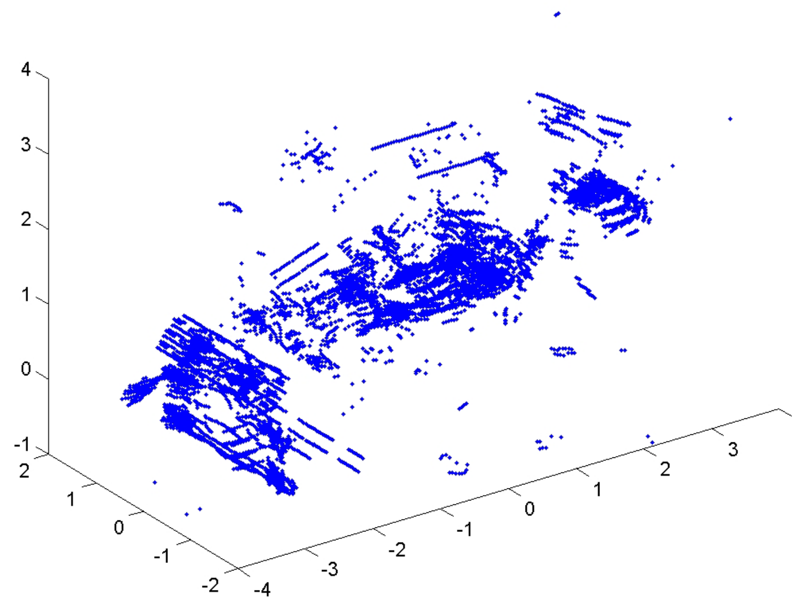
Model Order	1	2	3
Percentage of Resolution Cells	71.88	27.11	1.01

Nonuniform Elevation Sampling

- Narrow-angle imaging with the virtual interpolated flight paths
- use ESPRIT for height estimation



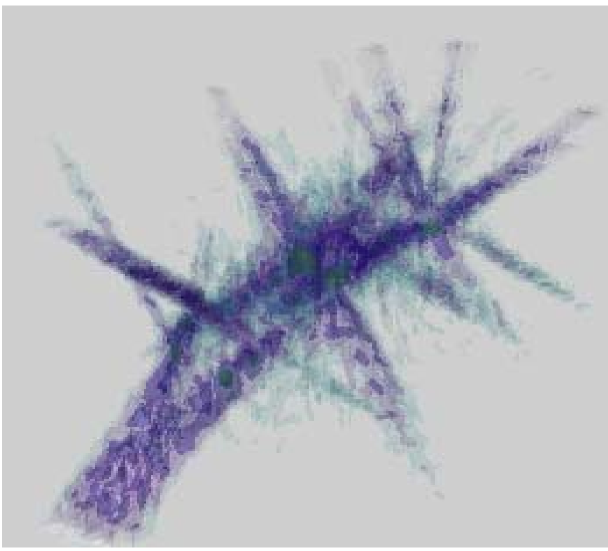


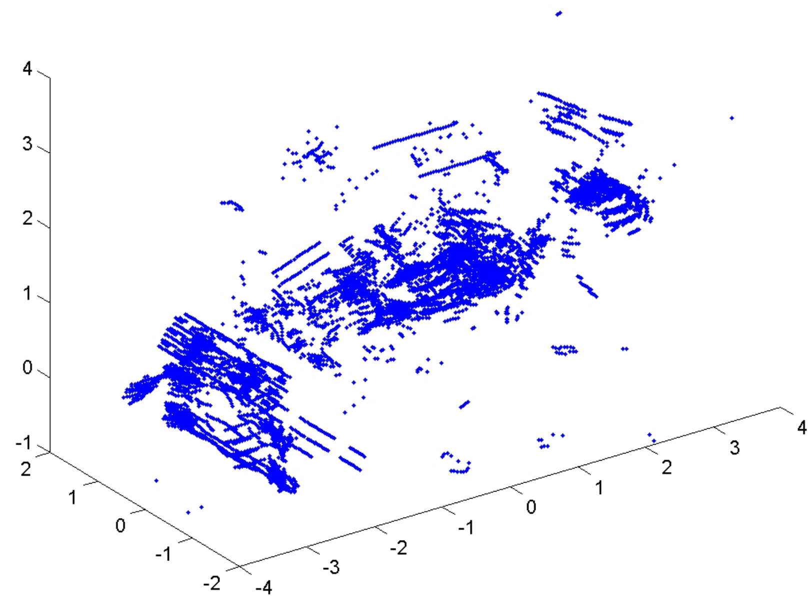


Model Order	1	2	3
Percentage of Resolution Cells	71.88	27.11	1.01

3D from Circular SAR

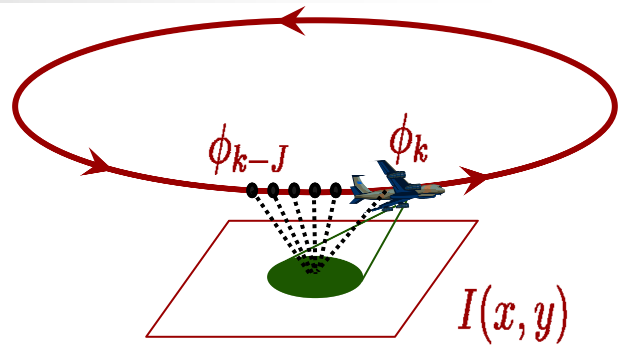
Ertin





Recursive Image Updating for Persistent Synthetic Aperture Radar Surveillance

Moses

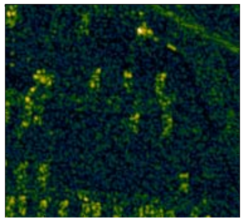


- Persistent SAR
  - SAR video
  - Imagery on demand
  - Variable aperture integration
- Insight: recursive imaging spreads computation over time and avoids block processing memory load

$$I_k = \lambda I_{k-1} + R_{\phi_k}$$

Convolution Backprojection

$$I_k(x,y) = \sum_{j=0}^{J-1} w_j R_{\phi_{k-j}}(x,y), \qquad (N \times N)$$



- Range profile by filtering and backprojecting

$$r_{\phi_j}(t) \rightarrow R_{\phi_j}(x,y)$$

- Window w_j controls crossrange sidelobes
- $J\,N^2$ computations per image
- Recursively:

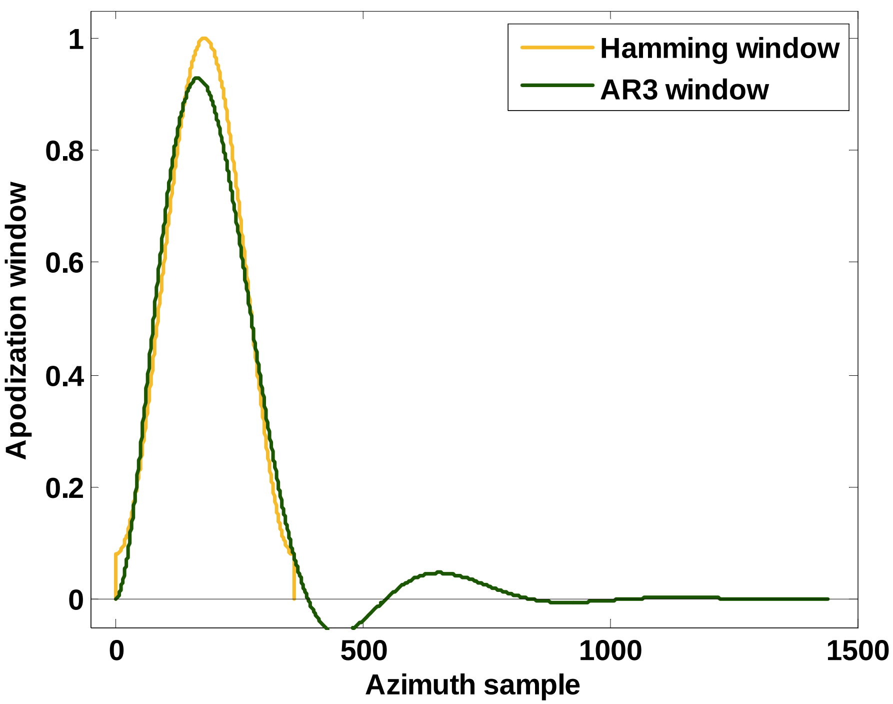
$$I_k = \sum_{m=1}^{M} \alpha_m I_{k-m} + \beta R_{\phi_k}, \qquad M \ll J$$

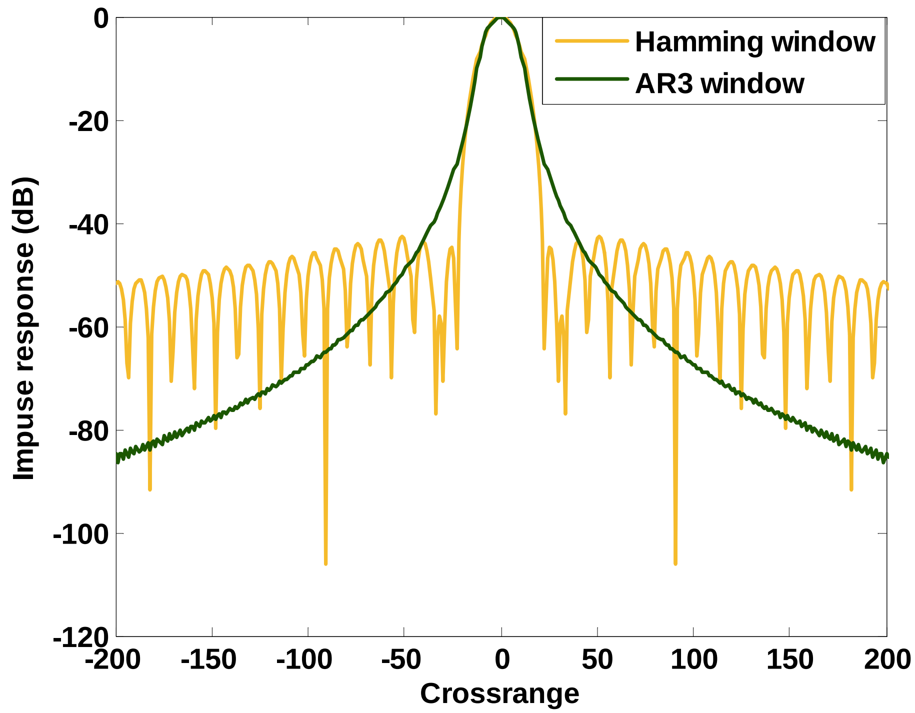
Third Order Recursion

Moses

$$I_k = \alpha_1 I_{k-1} + \alpha_2 I_{k-2} + \alpha_3 I_{k-3} + \beta R_{\phi_k}$$

- Can choose α_i coefficients to emulate many common apodization windows (e.g. Hamming).





GOTCHA C-SAR Video Snapshots

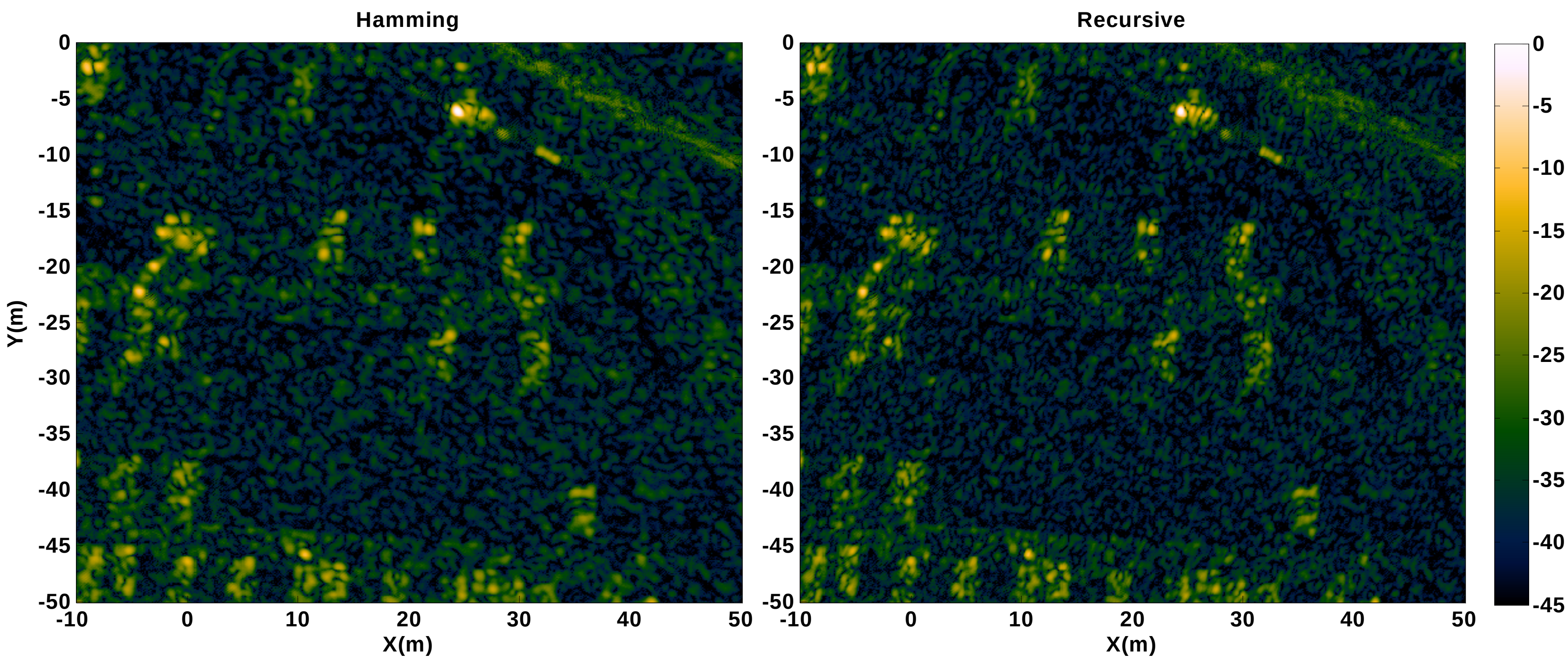
Moses

Block-Processing

Hamming Az Window

Recursive Processing

Third Order



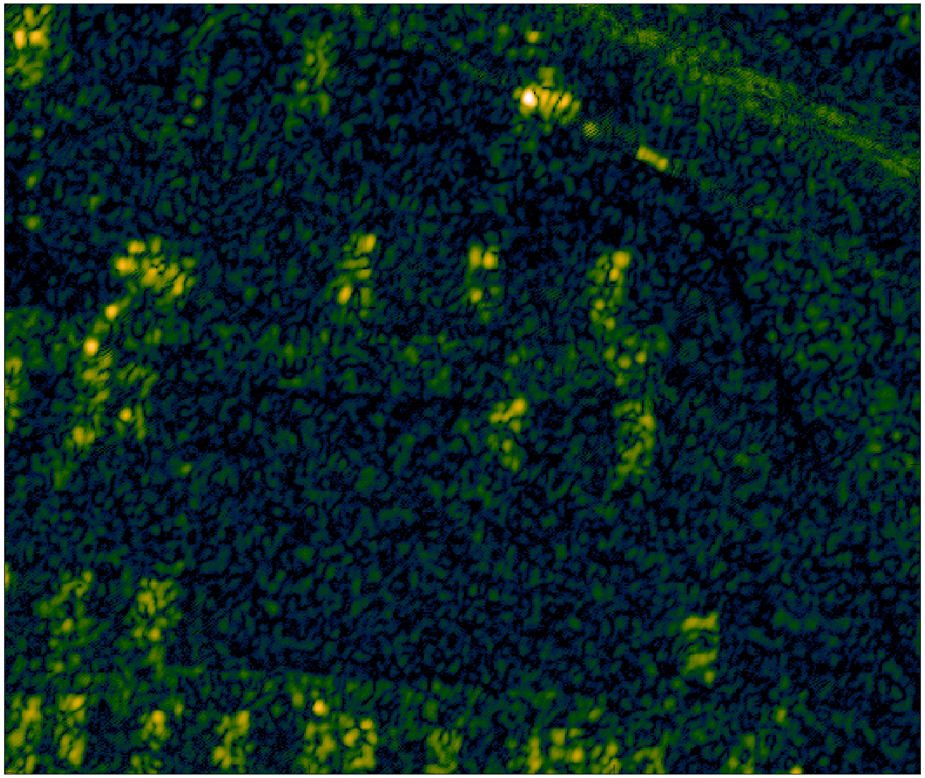
GOTCHA: f_c=9.6 GHz, 640 MHz BW, 45° elev, 3° azimuth

MURI: Integrated Fusion, Performance Prediction, and Sensor Management for Automatic Target Exploitation

Flop-free change in effective aperture

Moses

Recursive Processing
3° Azimuth Window



Recursive Processing
25° Azimuth Window

Enabling video SAR

Moses

- Memory
  - 5.9GB to 6.0MB (1000:1)
- Computation
  - Naturally distributed in time
- Consequence
  - Enable real-time, single-CPU, SAR video

Recursive Processing

25° Azimuth Window

Continuing aims

- Flexible processing responsive to fusion and management
  - Accept nonconventional apertures and frequency support
  - Incorporate priors or learn from data
  - Exploit nature's parsimony
  - Manage complexity
- Processing methods for complex scenes
  - Target motion
  - 3D scene structure
  - Anisotropic behavior
- Understanding of performance consequences of sensing choices
  - Pre-sensing impact of sensing choices for management (e.g. frequency *versus* geometric diversity)
  - Post-sensing estimates *and* uncertainties for fusion

What’s next …

- Multistatic processing
  - Imaging dynamic and anisotropic scenes
  - Reduction in computational complexity
  - Waveform diversity
- Nonlinear models
  - Exploit sparsity on low-dimensional manifolds
- Performance prediction
  - Expand scope of pre-sensing impact metrics
  - Posterior odds for parts matching
- Uncalibrated sensing
  - Addressing calibration uncertainty/mocomp