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

Sparse Reconstruction and Feature Extraction

MURI Review Meeting

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Clem Karl, Randy Moses

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Processing with purpose

ATE Objectives
Sensor Resources

Optimal, Robust Information Fusion (A. Willsky, lead)

- Graphical Models
- ...asures
- ...te Propagation
- ...els
- Learning and Adaptation

ATR/ATE Inferences
and Confidences

Problem formulations that admit context & priors

Features and
Uncertainties

Priors and
Learned Statistics

Measurement
Constraints

- ***Parametric and Nonparametric***
- ***Decision directed***
- ***Uncertainty characterization***

Adaptive Front-End Signal Processing (R. Moses, lead)

- Decision-directed Imaging and Reconstruction
- Modeling and Feature Extraction
- Statistical Shape Estimation

Management (D. Castanon, lead)

- Dynamic sensor allocation
- Efficient sensor management algorithms
- Multi-level planning
- Performance uncertainty

Kick-off Vision: Decision-Directed Imaging

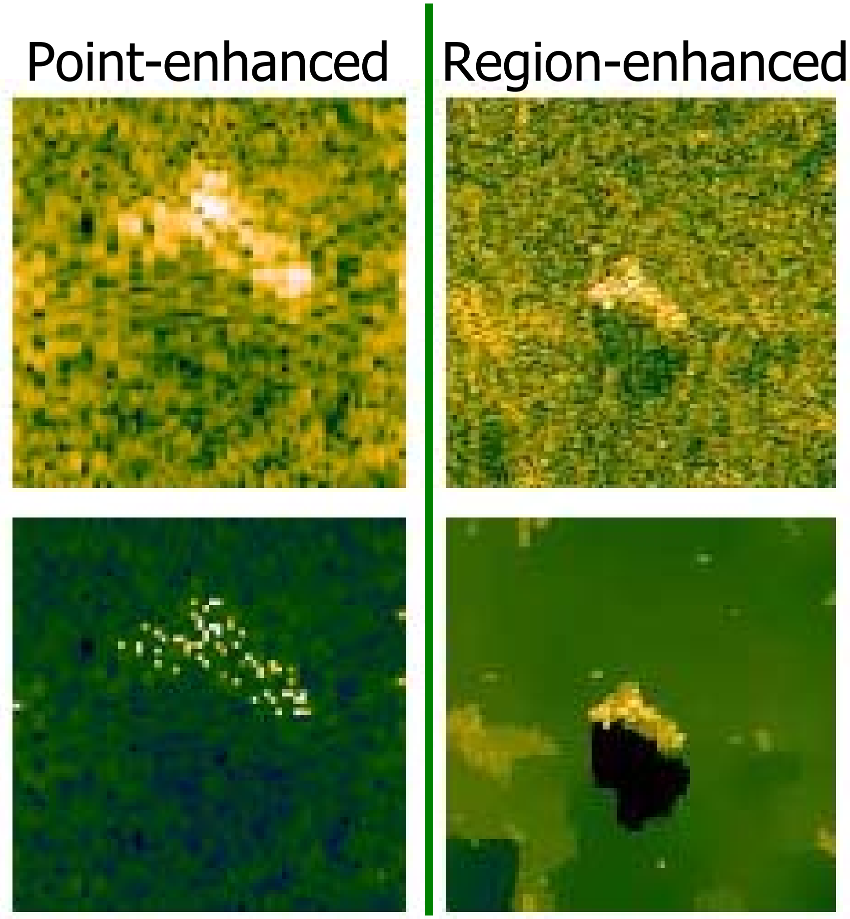
$$\hat{f} = \arg\min_{f} \{-\log p(g|f) + \Psi(f)\}$$

Changing $\Psi(f)$ changes image and enhances/suppresses features of interest.

$$J(\mathbf{f}) = \underbrace{\|\mathbf{g} - \mathbf{T}\mathbf{f}\|_2^2}_{\text{Likelihood: physical model and sparse representation}} + \underbrace{\alpha \|\phi(\mathbf{f})\|_p^p}_{\text{Prior (regularization)}}$$

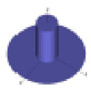
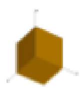
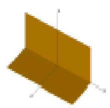
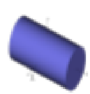
Likelihood: physical model and sparse representation

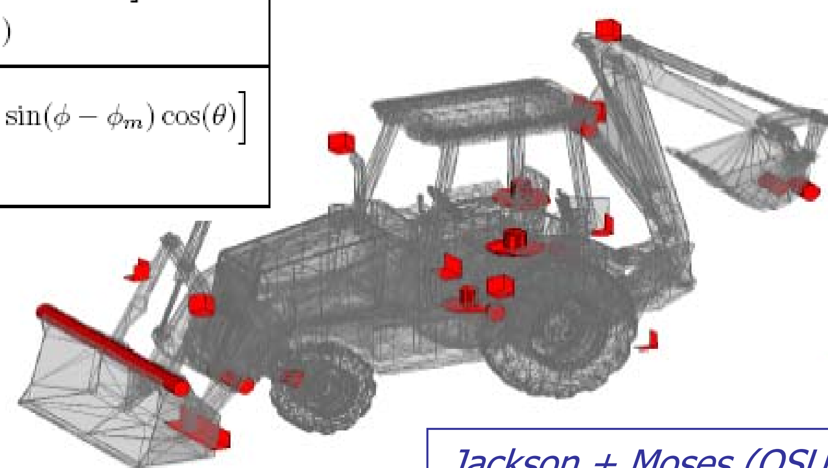
Prior (regularization)



Cetin (MIT) + Karl (BU)

Kick-off Vision: Sensor and Signal Models

Canonical Shape	Icon	Scattering Model $S_{T(m)}$
Top-hat		$S_{top} = \left(j\frac{f}{f_c}\right)^{1/2}\sin(\theta-\theta_m)$ $\theta\in(\theta_m,\theta_m+\frac{\pi}{4})$
Trihedral		$S_{trih} = \left(j\frac{f}{f_c}\right)\sin(\phi-\phi_m)\cos\theta\sin(\theta-\theta_m)$ $\theta\in(\theta_m,\theta_m+\frac{\pi}{4})\qquad\phi\in(\phi_m,\phi_m+\frac{\pi}{4})$
Dihedral		$S_{dih} = \left(j\frac{f}{f_c}\right)\sin(\theta-\theta_m)$ $\cdot\,\mathrm{sinc}\left[\frac{2\pi f}{c}L_m\cos\psi_m\cos\phi_m\sin(\phi-\phi_m)\cos(\theta)\right]$ $\theta\in(\theta_m,\theta_m+\frac{\pi}{4})\qquad\phi\in(\phi_m-\frac{\pi}{2},\phi_m+\frac{\pi}{2})$
Cylinder		$S_{cyl} = \left(j\frac{f}{f_c}\right)^{1/2}\mathrm{sinc}\left[\frac{2\pi f}{c}L_m\cos\psi_m\cos\phi_m\sin(\phi-\phi_m)\cos(\theta)\right]$ $\phi\in(\phi_m-\frac{\pi}{2},\phi_m+\frac{\pi}{2})$



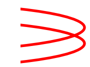
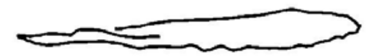
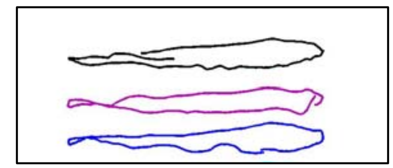
Jackson + Moses (OSU)

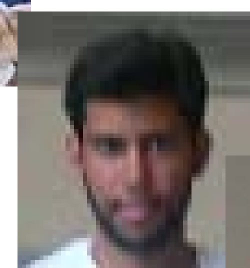
What did we say at the kickoff? What have we done? - I

- Statistical shape models
- Physics-driven basis sets for regularized inversion
  - Use prior information in basis sets
  - Extract object-level information
- Physical optics for model-based imaging
  - 3D
  - Sparse apertures
- Decision-directed feature extraction

Themes

- Posterior probabilities
  - Language for fusion
- Sparseness v. sparseness
  - Sparse apertures
  - Sparse signal representations
- Complexity reduction
  - 3D = 2+1
  - Dictionary grammar
  - Surrogate costs
- Directed processing
  - Adapt processing to priors, hypotheses

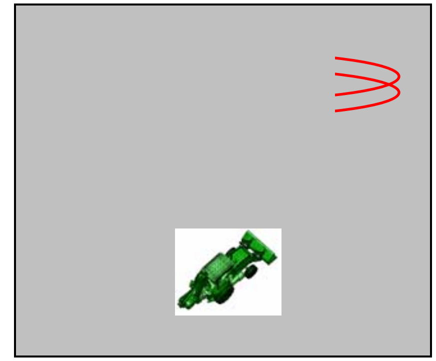





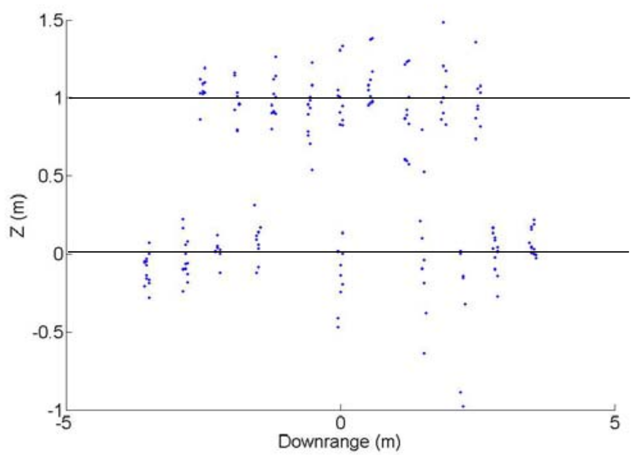


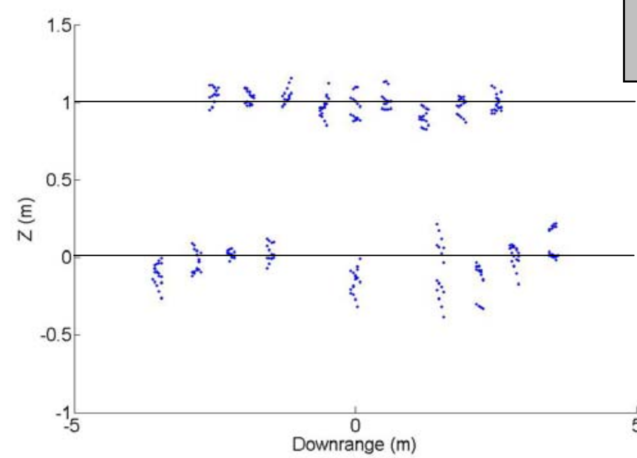

Ertin
Ramakrishnan

Sparse aperture: IFSAR

- Jointly reconstruct sparse IFSAR images with constraint on the pixel magnitudes



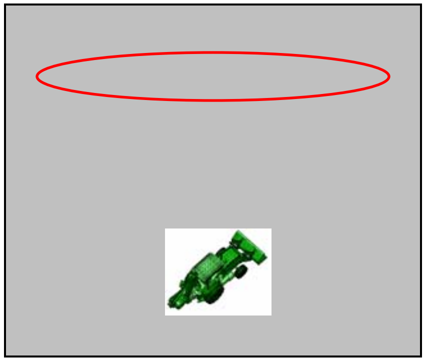




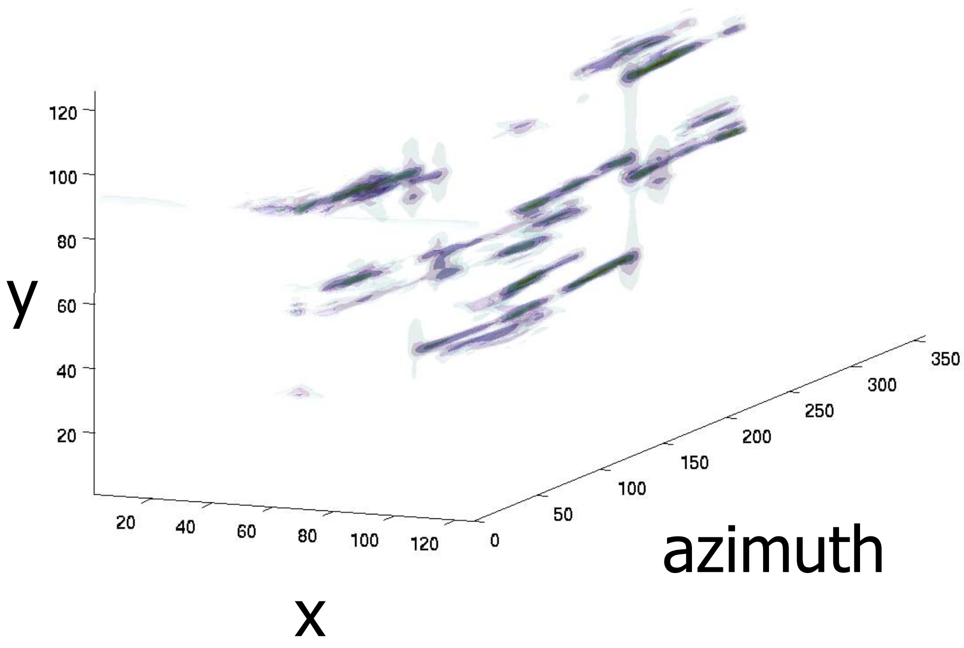
$$\arg\min_{\boldsymbol{f_1},\boldsymbol{f_2}} \quad \|\boldsymbol{g_1} - \boldsymbol{T_1}\boldsymbol{f_1}\|_2^2 + \|\boldsymbol{g_2} - \boldsymbol{T_2}\boldsymbol{f_2}\|_2^2 + \lambda_1^2\|\boldsymbol{f_1}\|_p^p + \lambda_2^2\|\boldsymbol{f_2}\|_p^p$$

$$\boxed{\text{subject to} \quad |(f_1)_i| = |(f_2)_i| \quad i = 1, \ldots, N}$$

Wide Angle Imaging



Traditional point scattering model is ill-suited to wide angle scattering



Karl

Priors: smooth aspect, sparse scattering

- Non-parametric, aspect-dependent imaging
- Formulation:

$$\hat{s}(x,y;\theta) = \arg\min_{s}\left[-\ln p(r \mid s) + J_{\text{aspect}}(|s|) + J_{\text{space}}(|s|)\right]$$

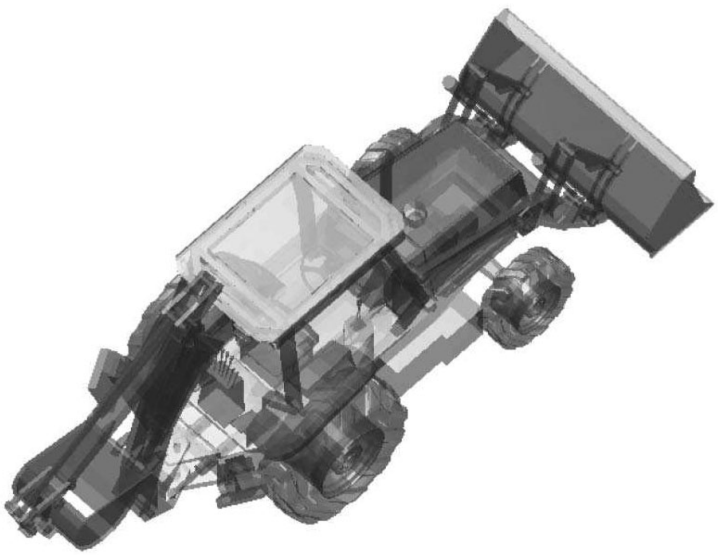
Data Model

Aspect Prior Knowledge

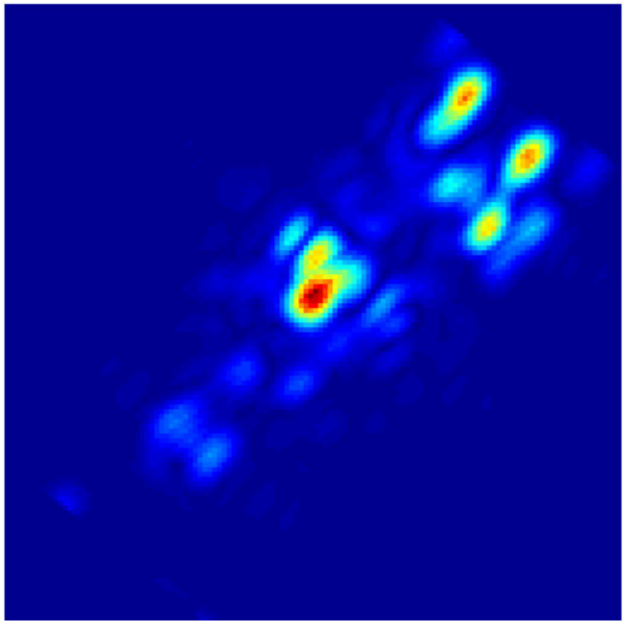
Spatial Prior Knowledge

  - J_{aspect}: e.g. piecewise smoothness of aspect dependent magnitude scattering behavior
  - J_{space}: e.g. spatial sparsity of magnitude scattering behavior

X-Patch Backhoe Example



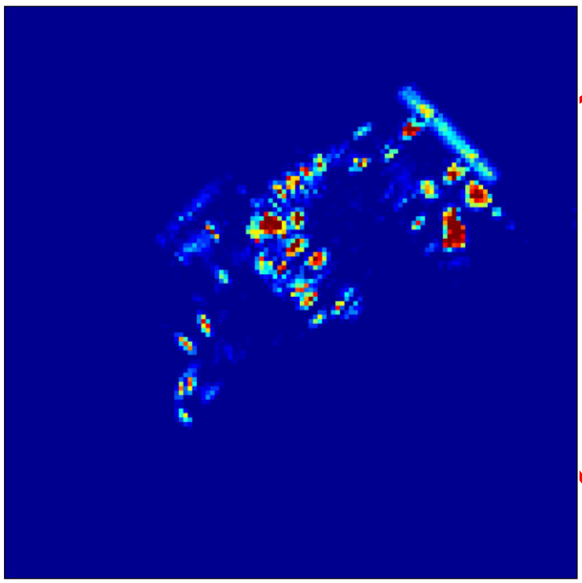
Backhoe CAD Model



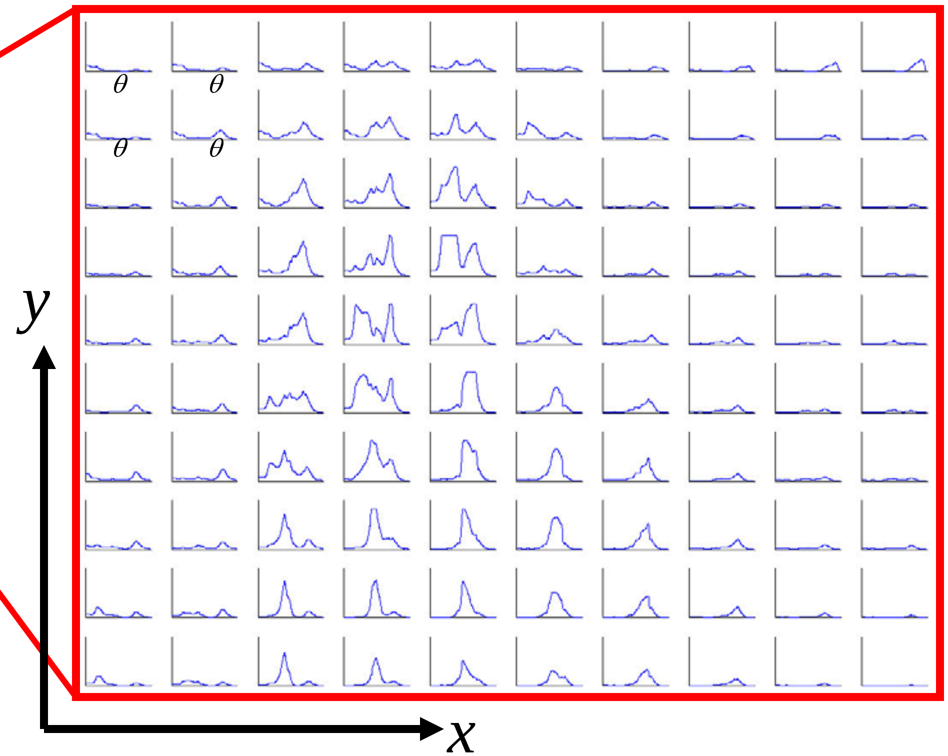
Conventional Polar-Format Image
Azimuth extent: 5^{o}
Bandwidth: 500MHz

X-Patch Backhoe Example

Wide aperture 110°



Aspect dependent imaging
Azimuth extent: 110°
Bandwidth: 500MHz



Aspect dependent scattering behavior from indicated sub-region

X-Patch Backhoe Example

Wide aperture 110°

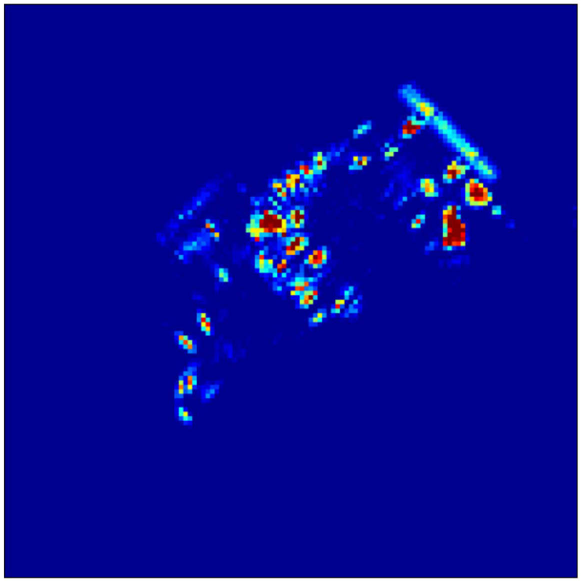
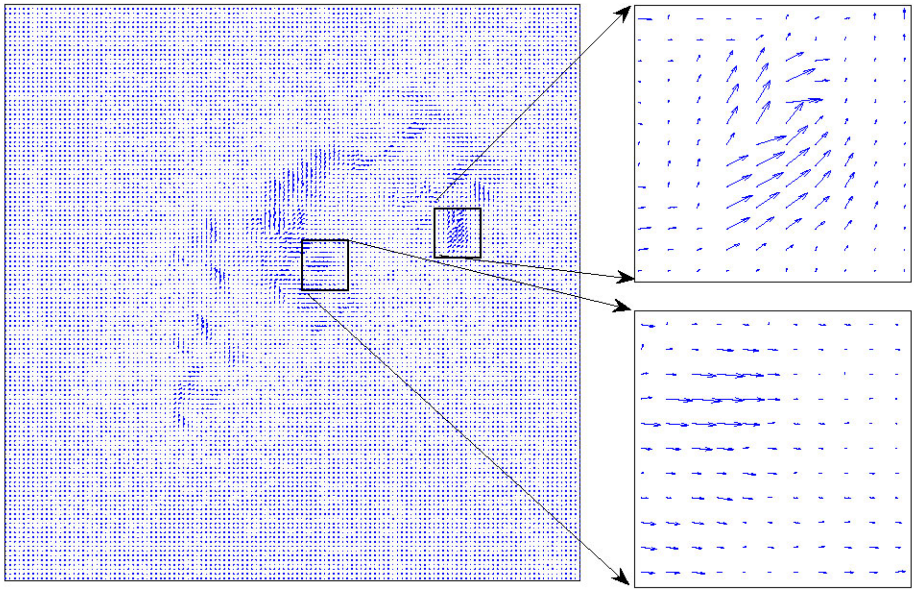


Image of maximum aspect change

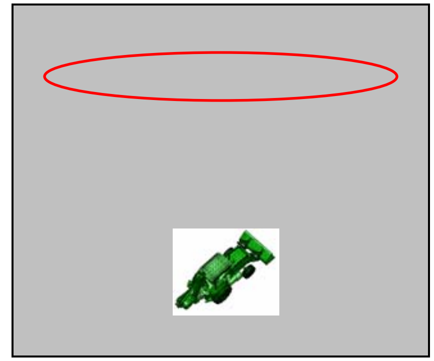


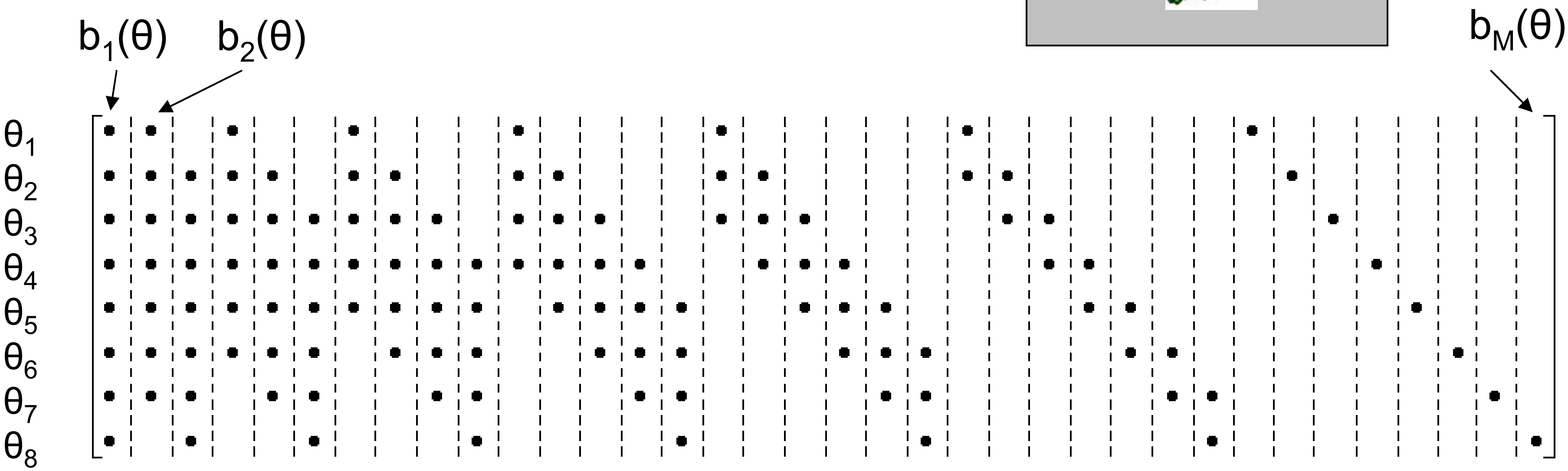
Quiver plot of magnitude and direction of scattering field

Anisotropic scattering: Dictionary + “grammar”

Varshney
Cetin

- Incorporate into dictionary prior information about scattering behavior



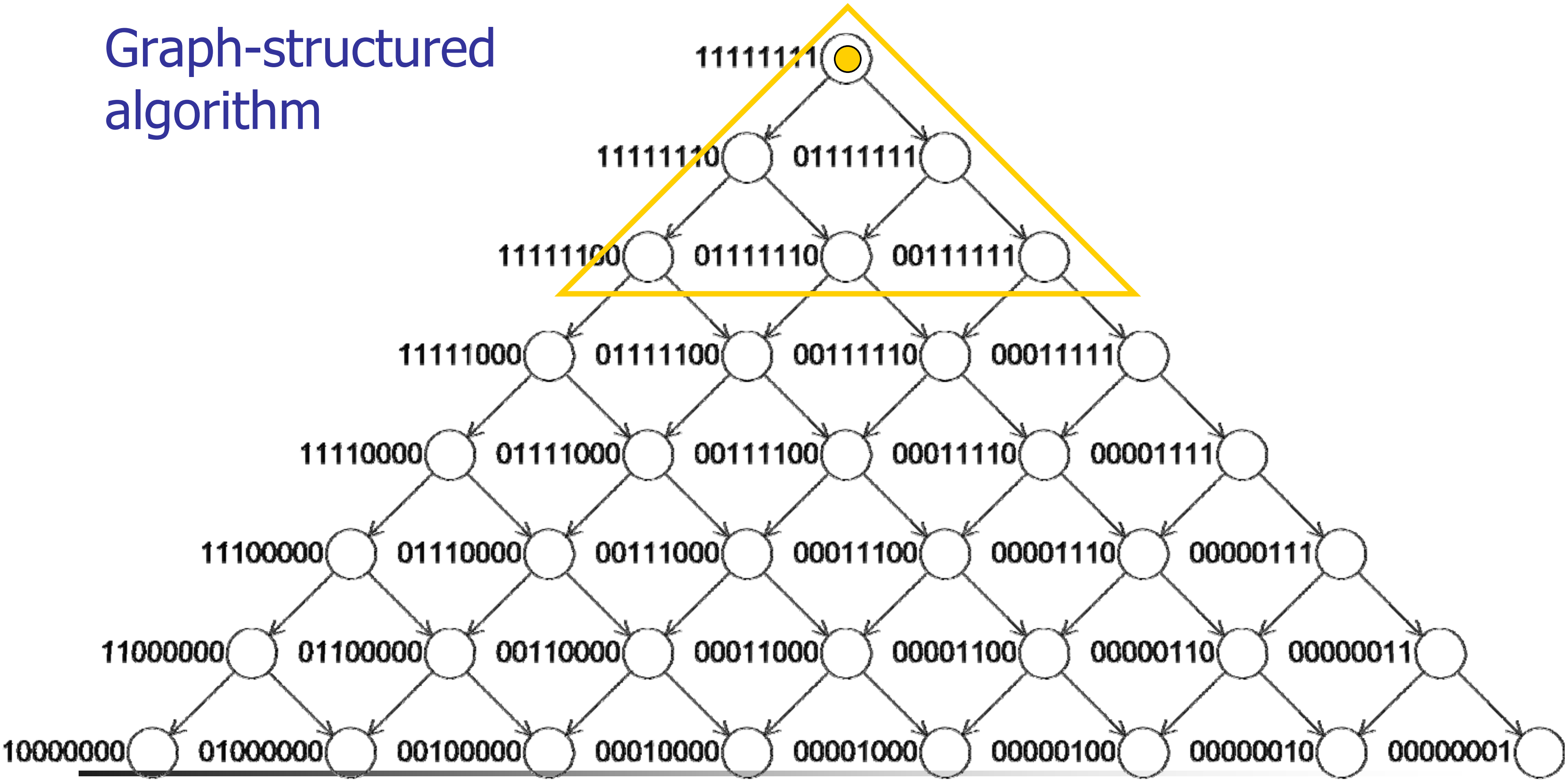


NxM matrix M=N(N+1)/2

Anisotropic scattering

Varshney
Cetin

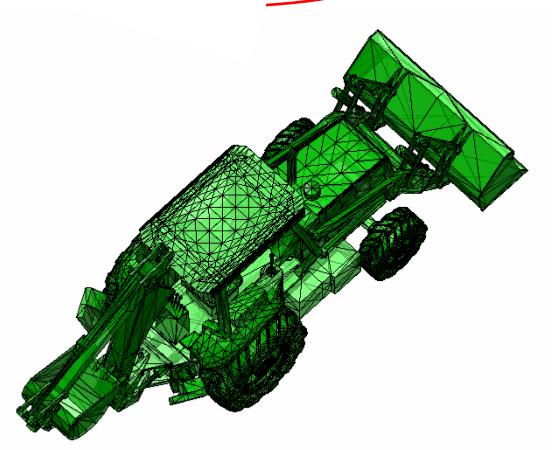
Graph-structured algorithm

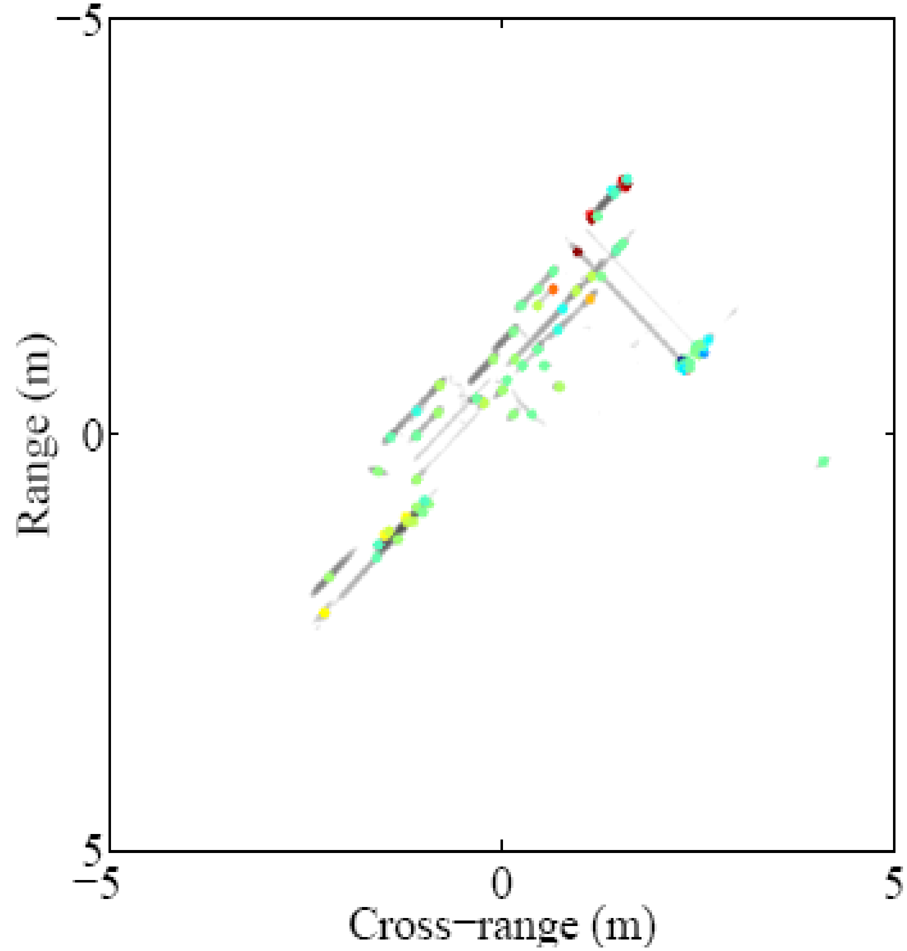


Example results -1

Varshney
Cetin

Wide aperture 110°



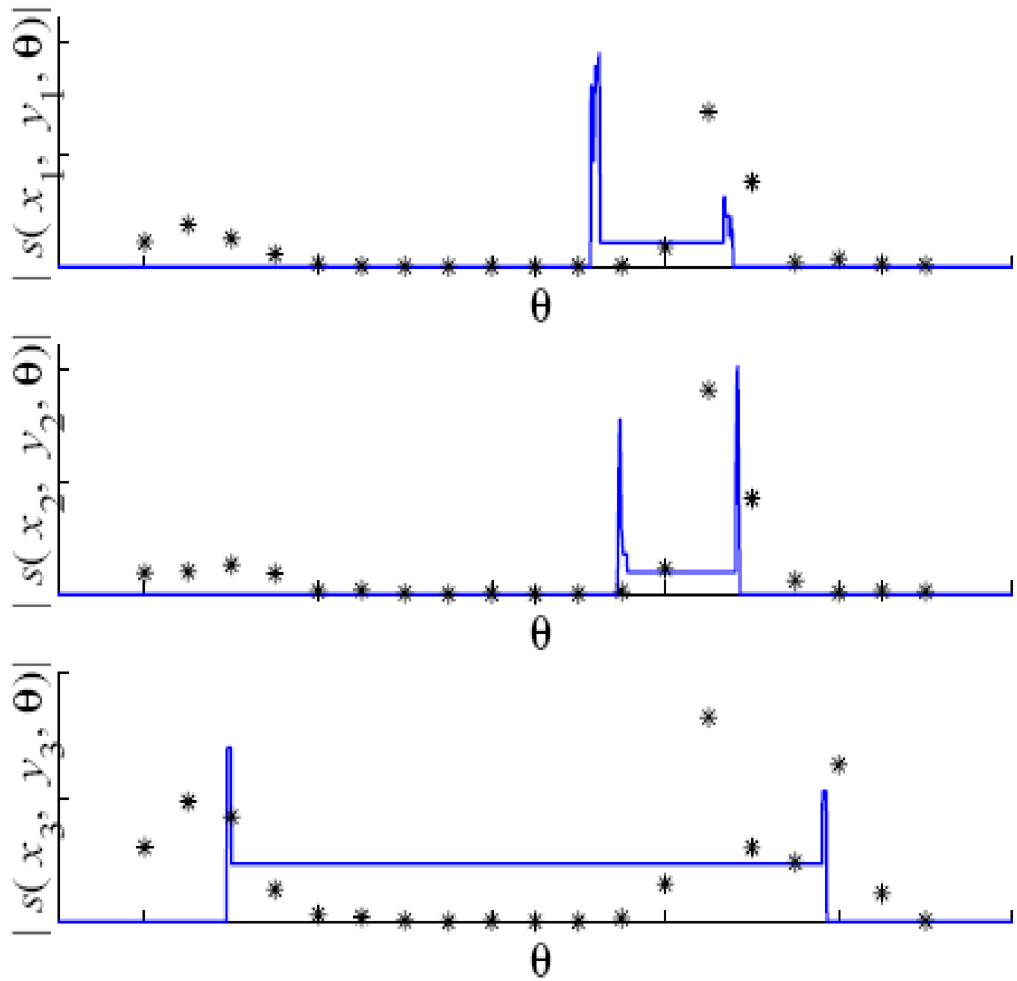


- Process: Threshold image to dominant 75 reflectors
- Visualize: Color-coding of scattering direction

Varshney
Cetin

Example results -2

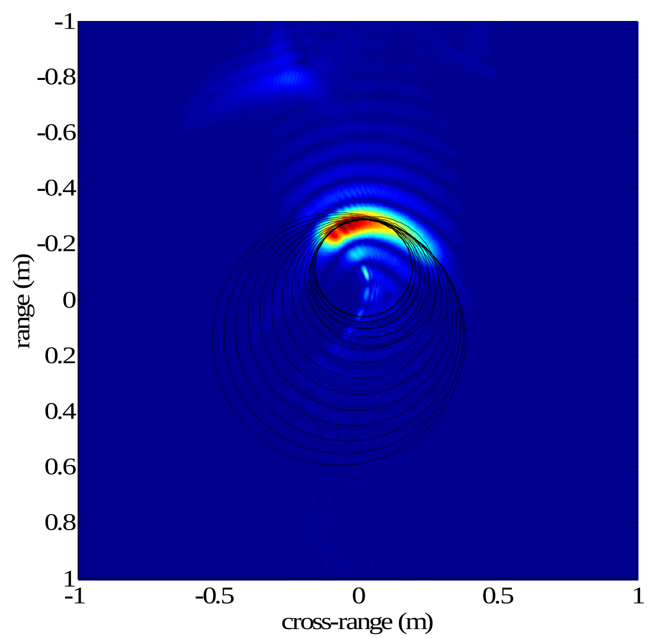
- Estimated scattering functions of three scatterers

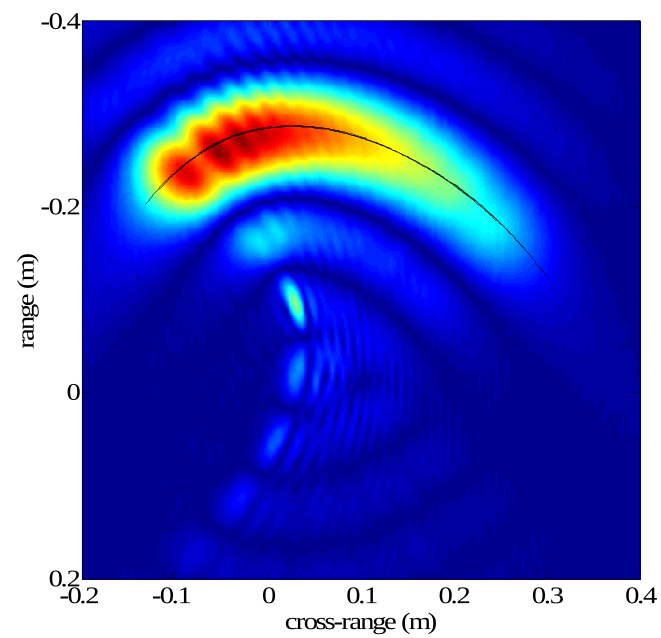


Other dictionaries: migrating phase centers

Varshney
Cetin

- Characterize reflector migration over subapertures



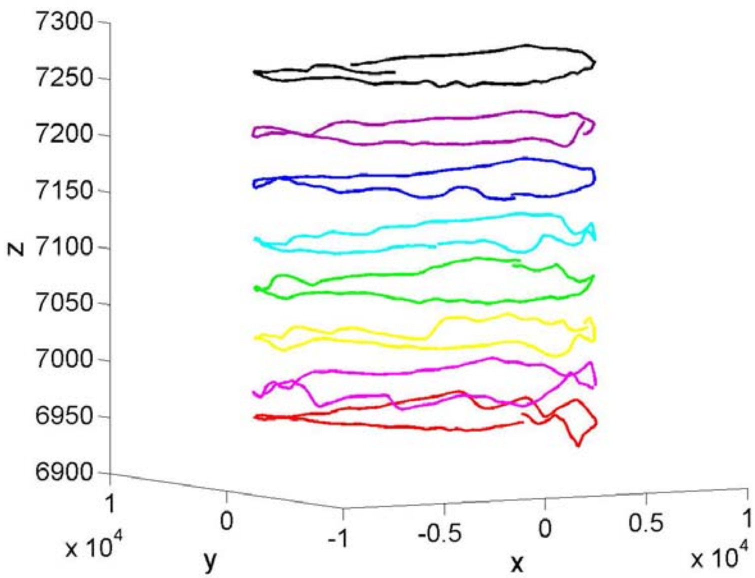


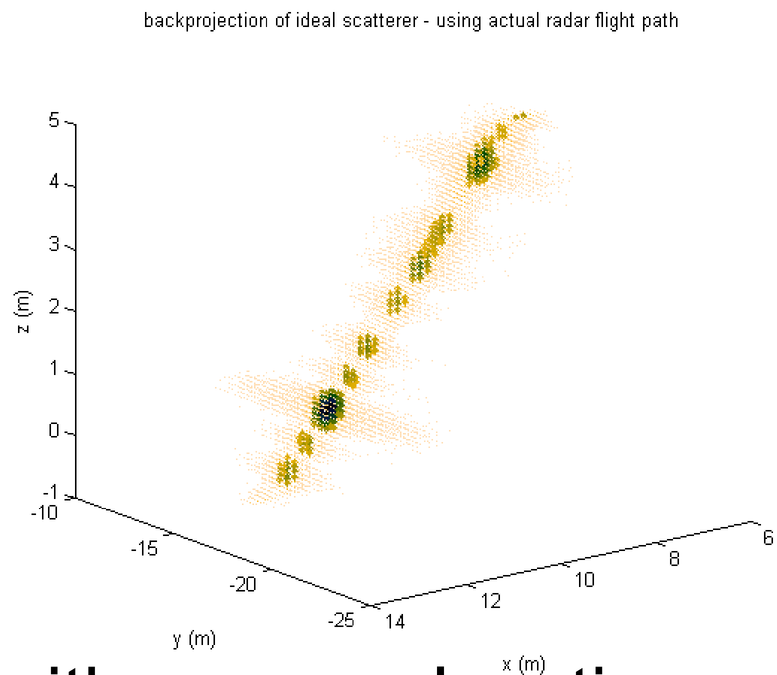
Internal summary: wide angle SAR

- Jointly characterize location and anisotropy from wide-angle SAR
  - Sparse signal representation for inversion
  - Model anisotropy using overcomplete dictionary

  - Approximate, graph-structured algorithm
  - Migratory atoms in overcomplete dictionary
  - Hough space regularization for glint anisotropy (have not described here)

Volumetric imaging

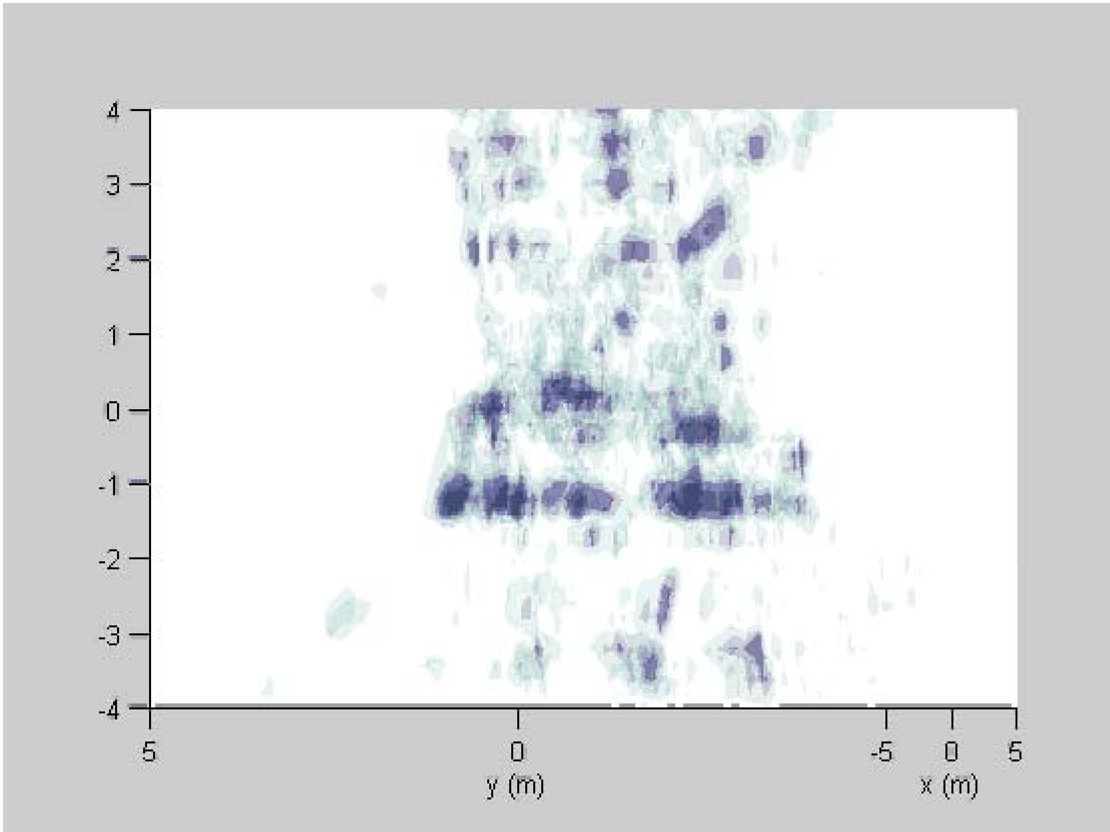




- Nonlinear flight paths with sparse elevation sampling; aliasing and high side lobes in slant plane height

Volumetric Imaging

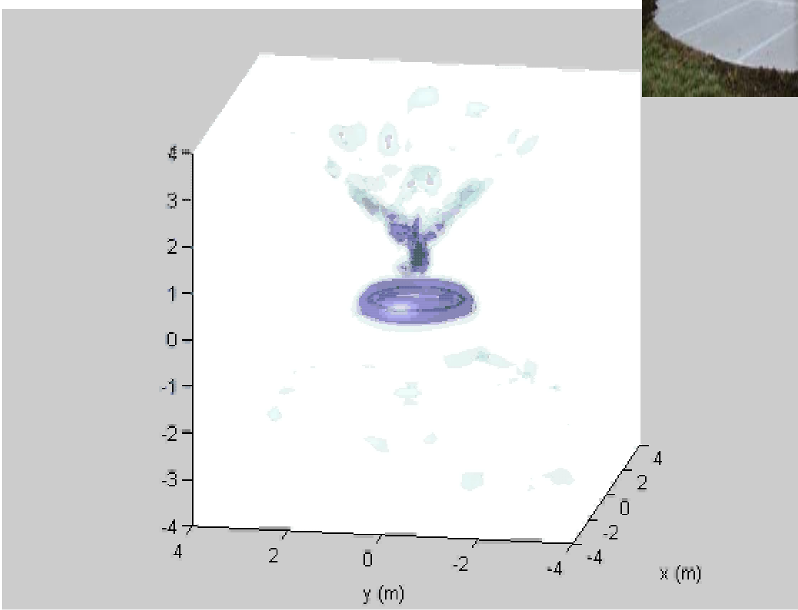
Coherent 360° image of a Taurus using all 8 elevation angles.



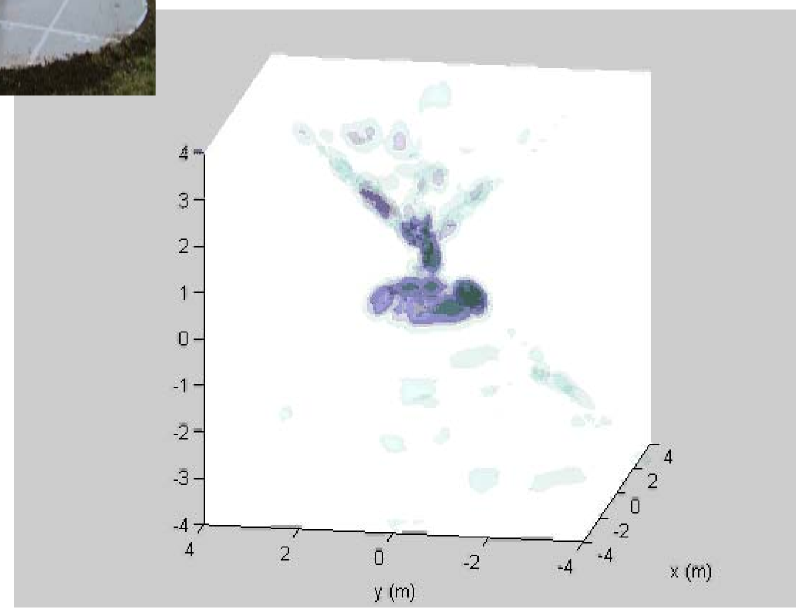
Volumetric Imaging

Austin SET

Coherent 360° images using all 8 elevation angles.



Ideal tophat simulated using actual radar flight path

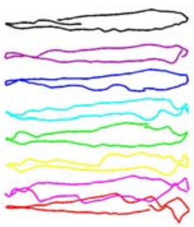


Measured tophat

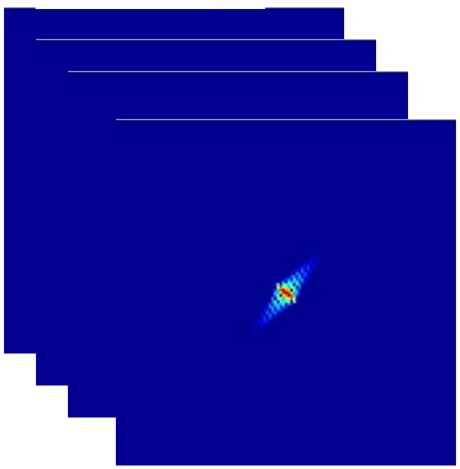
3D nonparametric processing

Ertin

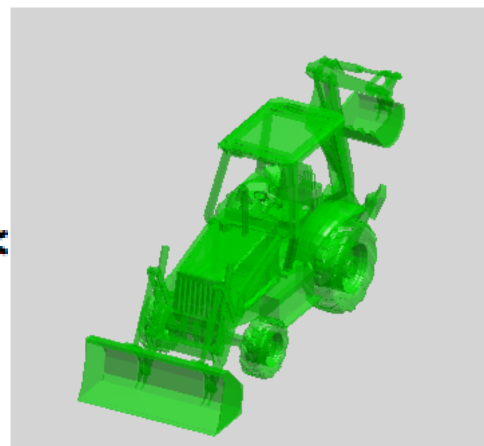
Extension of nonquadratic regularization based image reconstruction methods [Cetin & Karl, 2001] to 3D



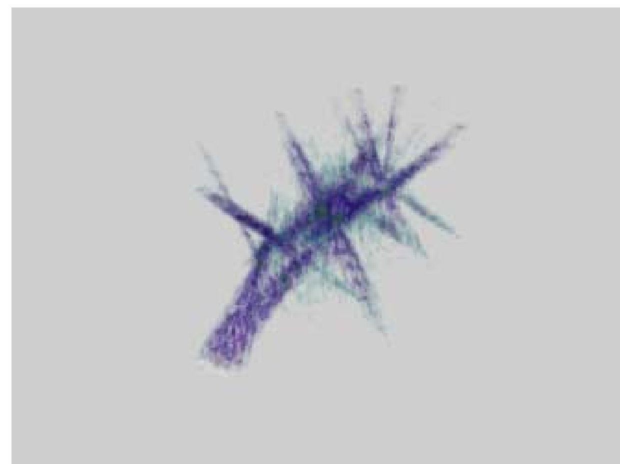
$$\arg\min_{x}\{\|H * x - y\|^2 + \lambda\|x\|^p\}$$



$*$



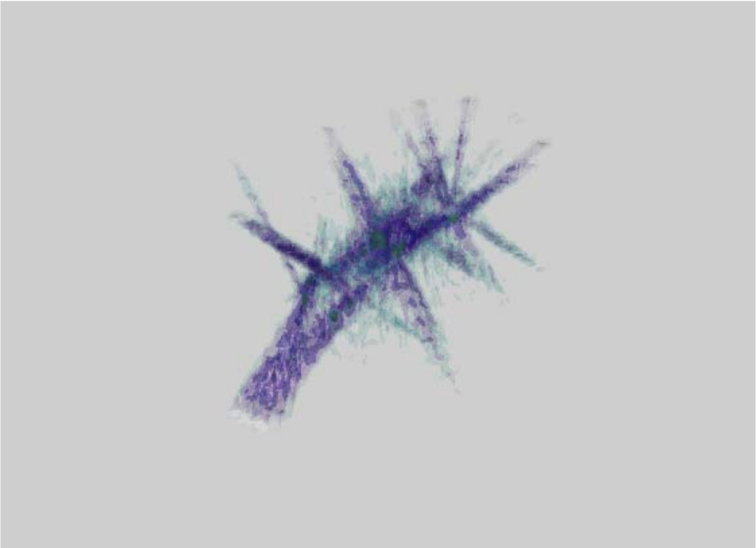
$\approx$



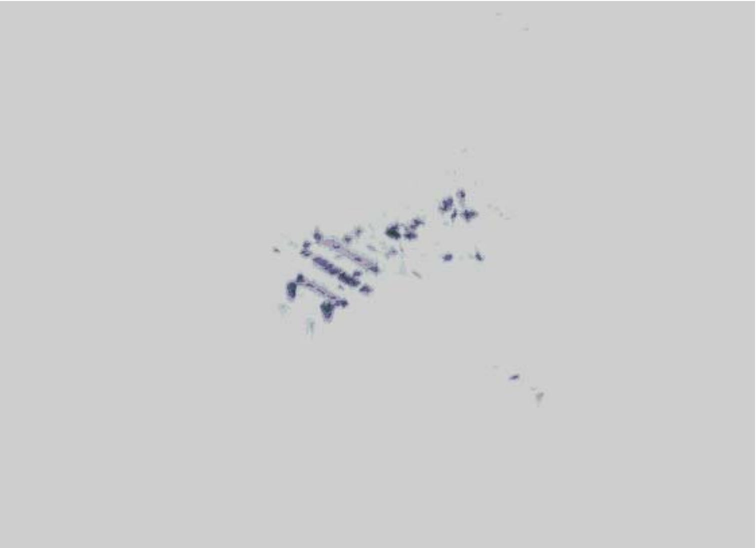
Multi-pass forward model

3D nonparametric processing

Ertin



Backprojected Image



Sparse Reconstruction

Multi-Pass: model-based imaging

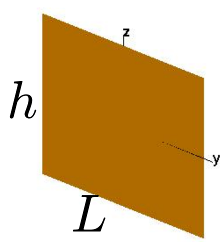
Jackson
Sharma

$$S = \sum_m \begin{bmatrix} A_{vv} & A_{vh} \\ A_{hv} & A_{hh} \end{bmatrix} S_{T(m)}(f, \theta, \phi; \Theta_m) \exp\left(\frac{-j2\pi f}{c} \Delta R_m\right) = \begin{bmatrix} S_{vv} & S_{vh} \\ S_{hv} & S_{hh} \end{bmatrix}$$

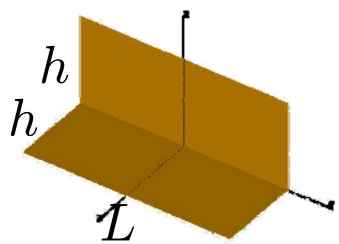
Polarization — Frequency and Aspect Dependence — Linear Phase term

$S_{T(m)}$ depends on type of reflector

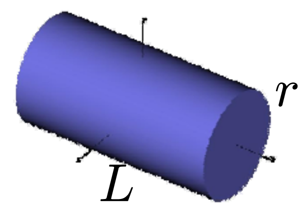
Plate



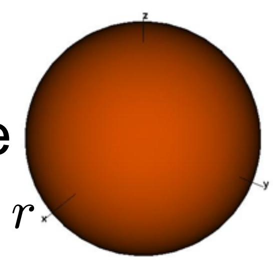
Dihedral



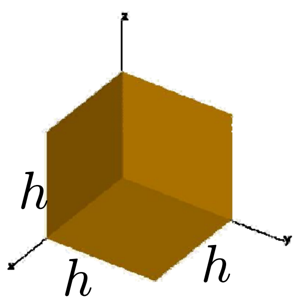
Cylinder



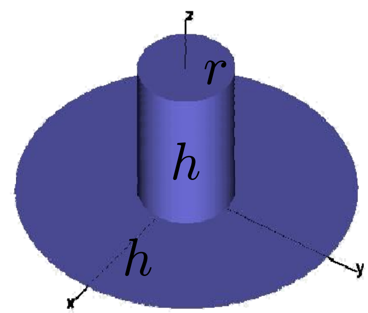
Sphere



Trihedral

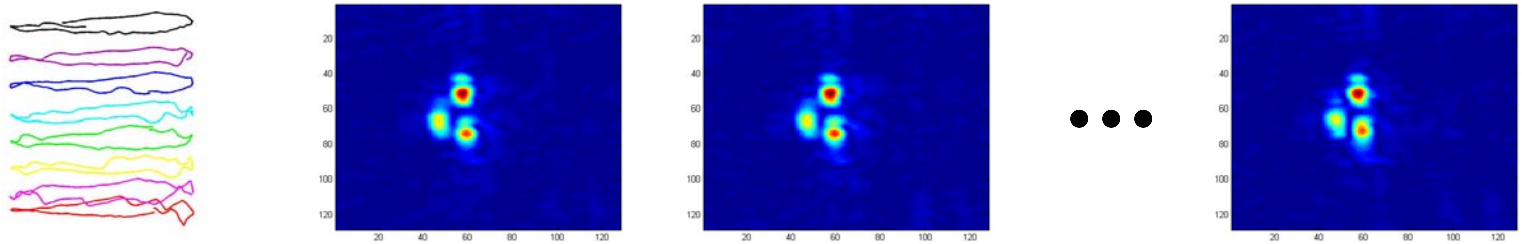


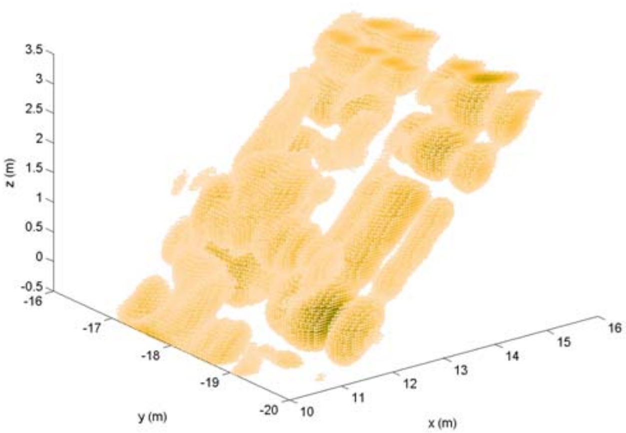
Top-hat



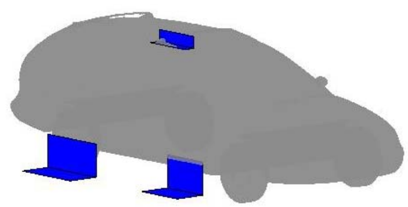
Multi-Pass: model-based imaging

Sharma
Potter





VSAR Image



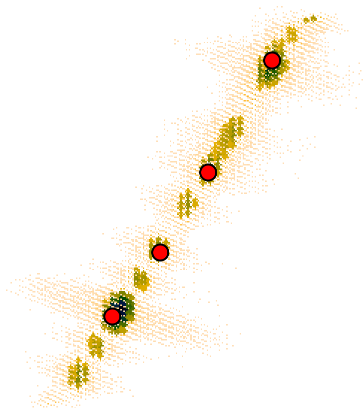
Parametric
Model Fit

Posterior Cramér-Rao bound provides feature uncertainties

Sharma
Potter

Managing regression complexity-1

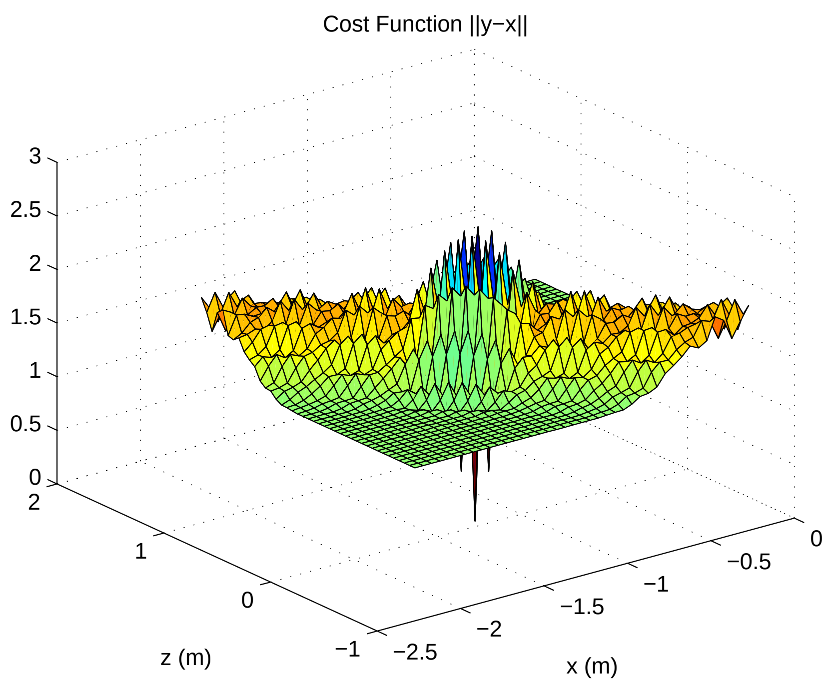
- Nonconvex regression for {x,y,z,L,φ} at each reflector
  - Initialize using dictionary and noncoherent greedy selection
  - Design dictionary using Fisher information for parametric model

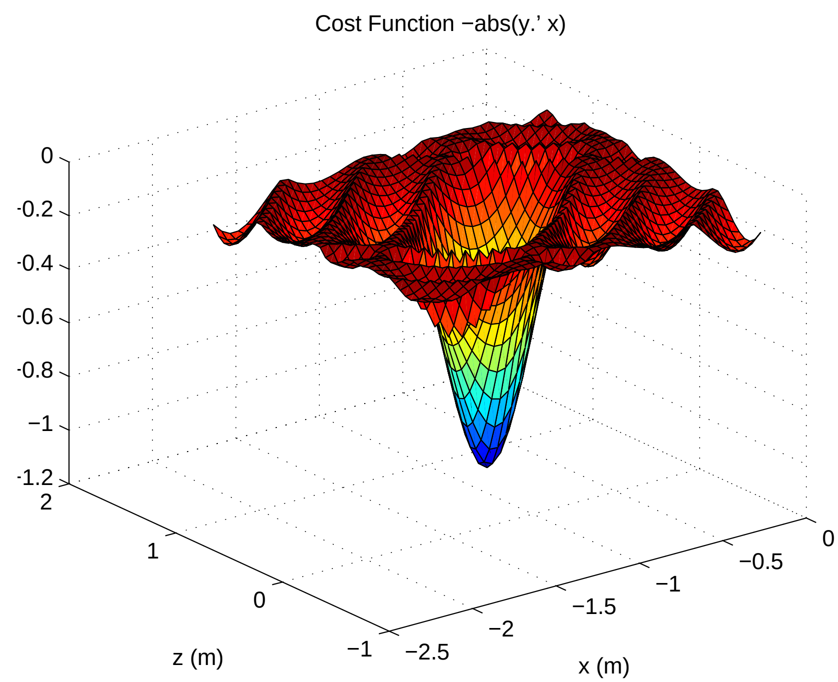


Managing regression complexity-2

Sharma
Potter

- Surrogate cost function for nonconvex regression



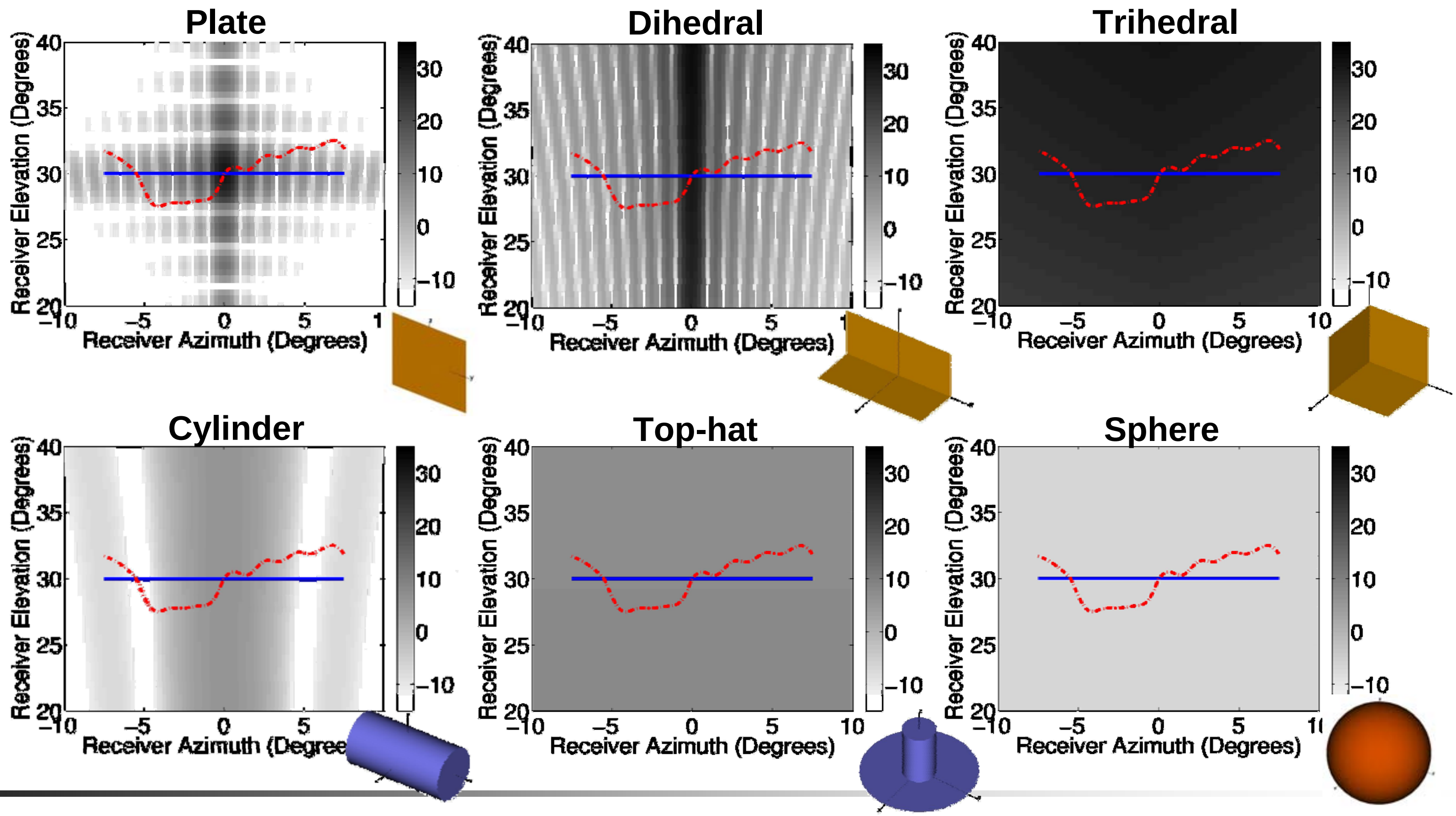


Expanding dictionaries

Jackson
Moses

Linear Flight Path

Nonlinear Flight Path



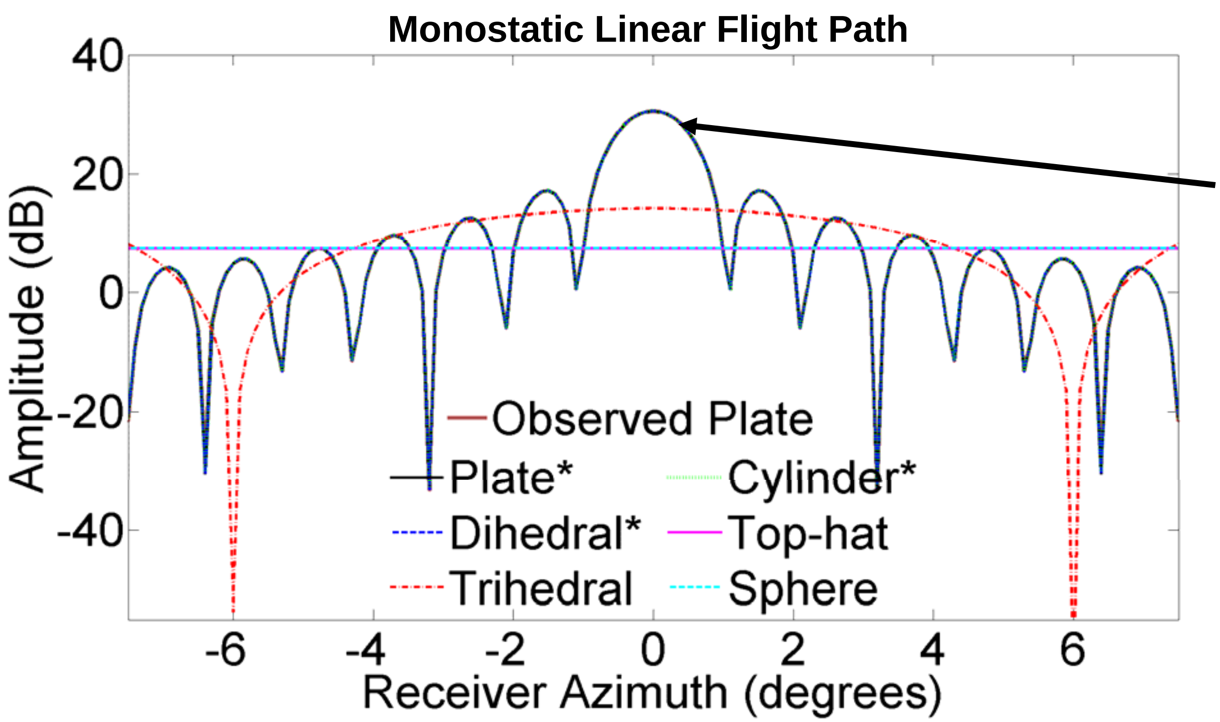
Correlation and ambiguity

Jackson
Moses

Easily confused best-fit features

True Signal	Model Fit Errors (dB)					
	Plate	Dihedral	Trihedral	Cylinder	Top-hat	Sphere
Plate	-43.0668	-42.3765	15.1250	-41.6044	15.6085	15.6083
Dihedral	-16.9800	-16.9292	15.1074	-19.7509	15.6003	15.6001
Trihedral	-14.5679	-14.6323	-26.6534	-20.3218	1.0707	6.3117
Cylinder	-25.9517	-29.6208	-15.2579	-29.6863	-5.8281	-5.8310
Top-hat	-13.7339	-15.4873	-14.7378	-11.8658	-15.6206	-14.5147
Sphere	-16.0719	-37.9948	-28.3642	-38.0509	-33.1546	-38.3475

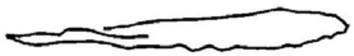
Multiple models may fit well to the observed feature

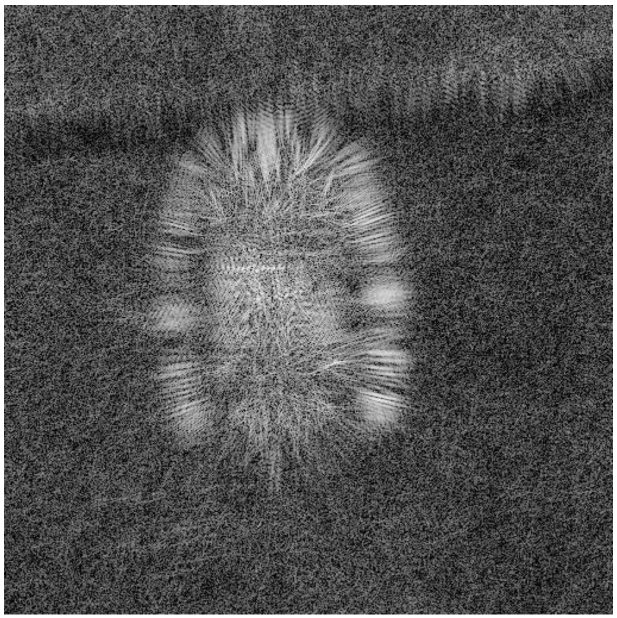


e.g. Plate, Cylinder, and Dihedral all have length-dependent sinc responses

Context-directed imaging

Ertin
Potter





Single orbit image [Gotcha]

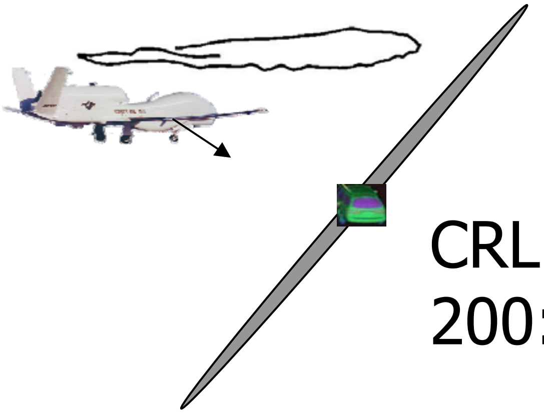
?

?

?

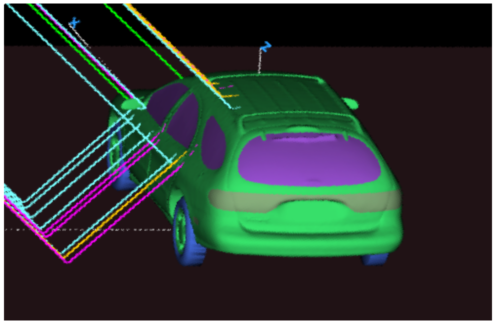
Context-directed imaging

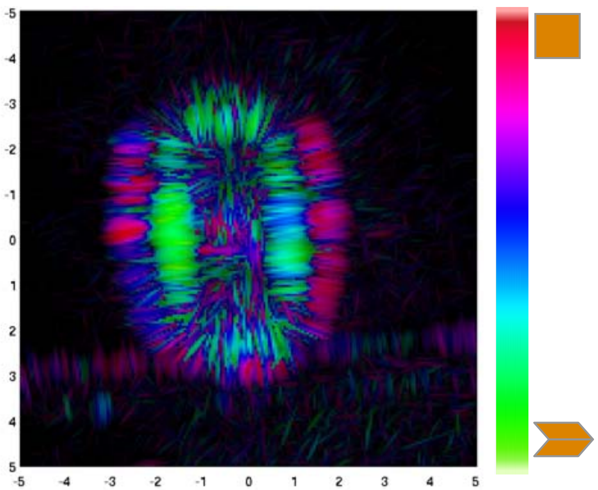
Ertin
Potter



CRLB ellipse
200:1 at 4°

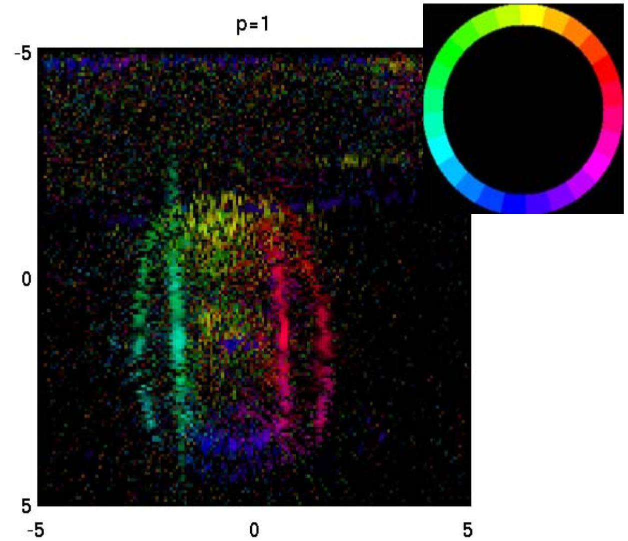
GO/PO
physics





Odd bounce

Even bounce

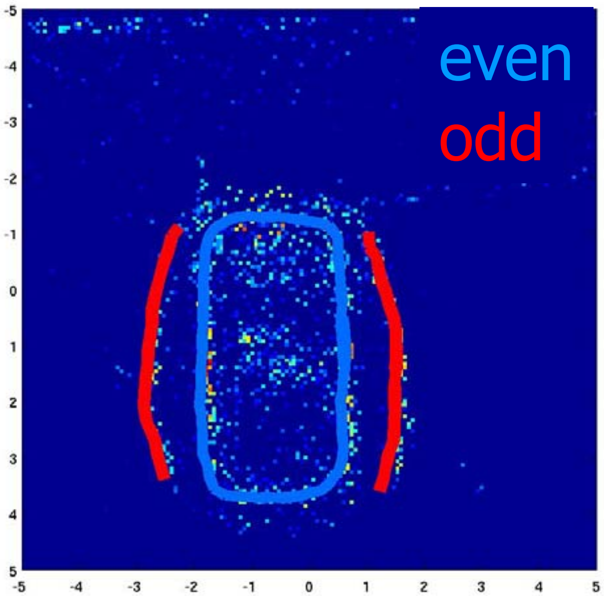


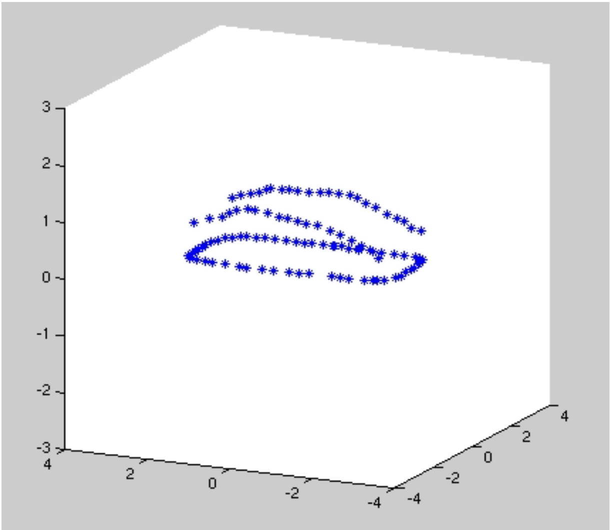
Polarization

Angle

Context-directed imaging

Ertin
Potter





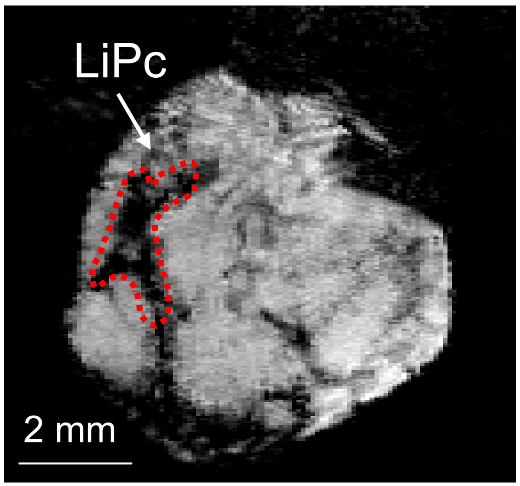
Object model: vertically aligned one- and two-bounce reflectors

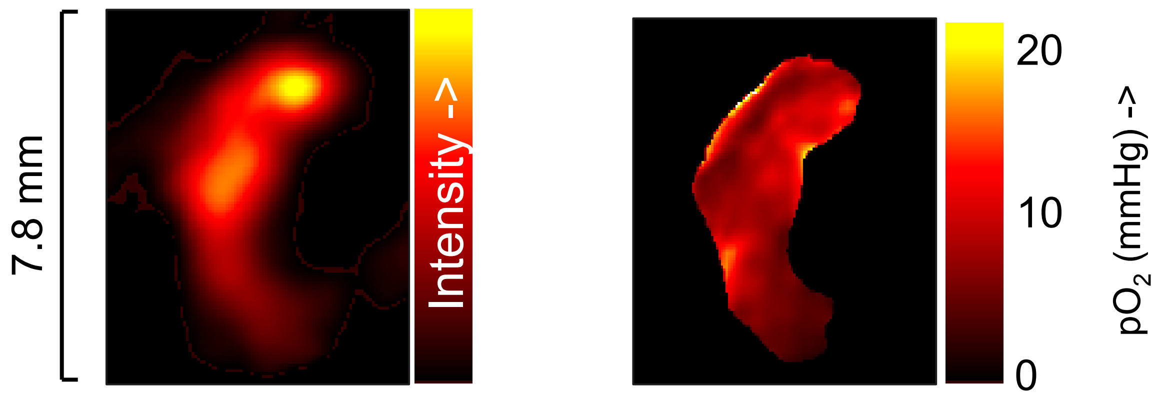
➡ 3D from layover

Transferring insight

Som Potter

- Electron paramagnetic resonance for medical imaging
  - Guide radiation therapy for tumors
  - Non-invasively monitor stents in coronary arteries





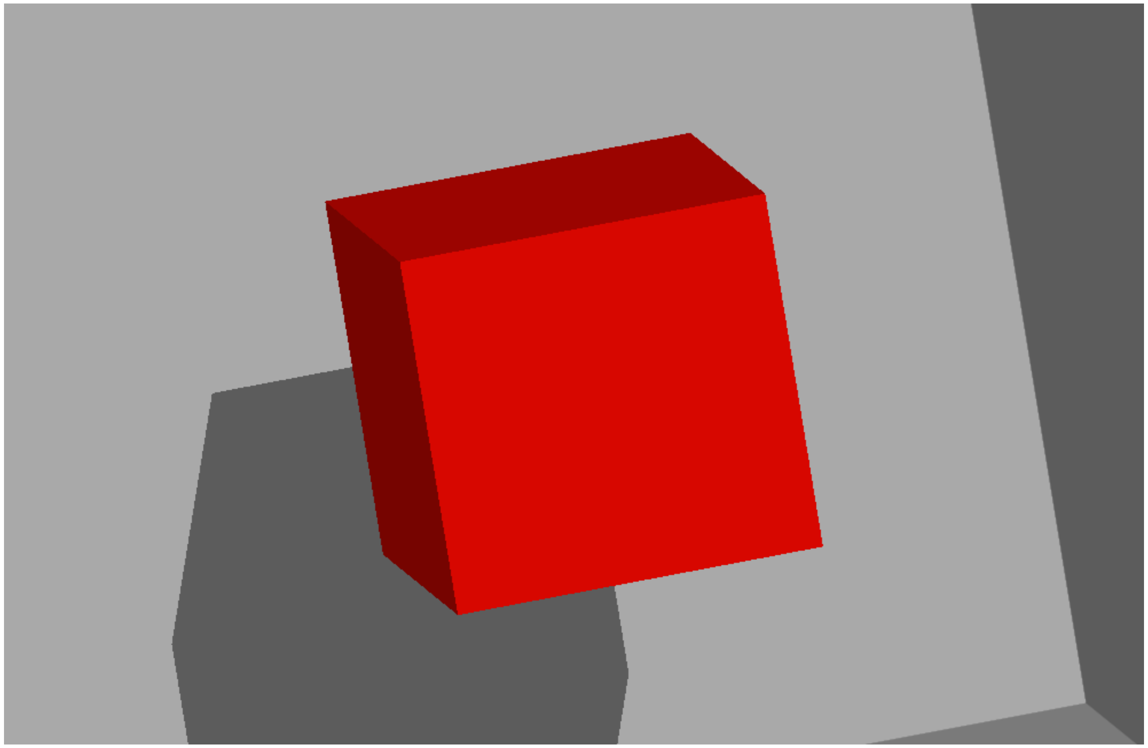
Probe Distribution **Carbogen-breathing**

In vivo imaging of oxygen concentration in tumor

- Goal: accurate estimates with fast acquisition.

Spin resonance example -1

Som Potter

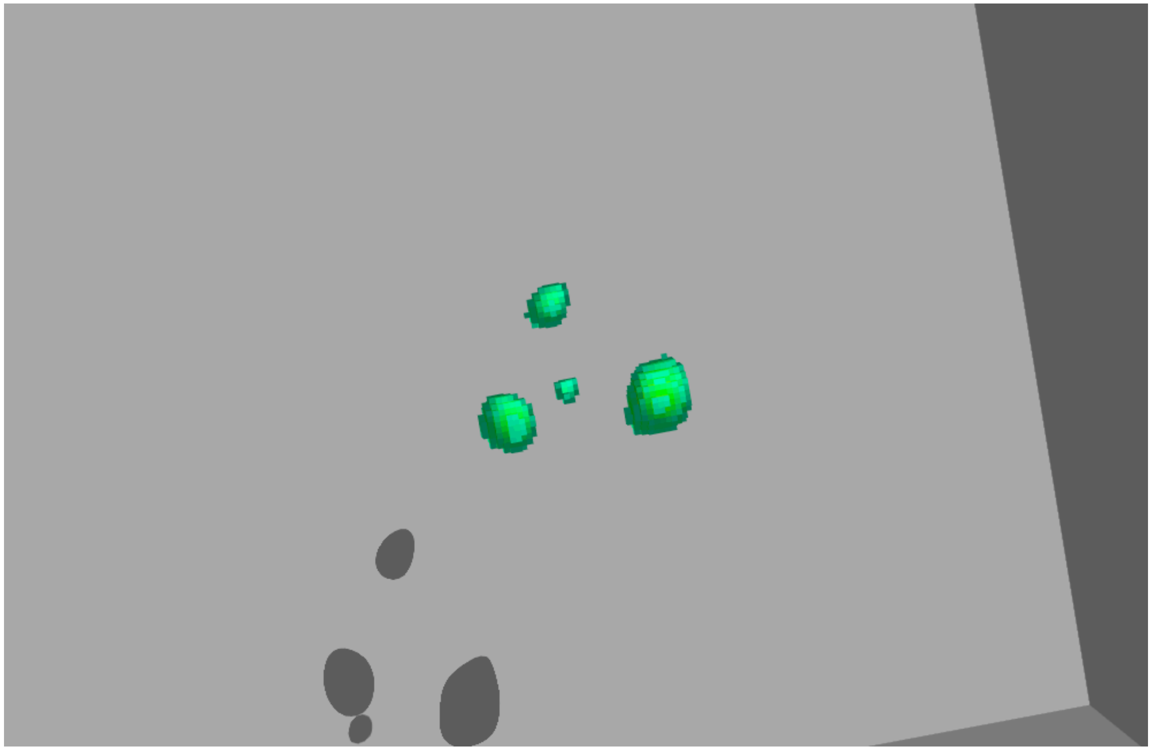


Signal is sparse in the field-of-view.

40:1 reduction in data acquisition time

Som
Potter

Spin resonance example - 2



- L-band spectrometer, 13 projections.
- Initialization: regularized least-squares with constant line-shape
- Nonlinear regression: 3D iterative spatially variant reconstruction

Themes

- Posterior probabilities
  - Language for fusion
- Sparseness v. sparseness
  - Sparse apertures
  - Sparse signal representations
- Complexity reduction
  - 3D = 2+1
  - Dictionary grammar
  - Surrogate costs
- Directed processing
  - Adapt processing to priors, hypotheses

What's next - I

- Regularized linear inversion
  - Automatic hyperparameter choice
  - Errors in sensing model parameters
  - Learn scattering functions from data
  - Design dictionary from target hypotheses
  - Anisotropic penalties in 3D & 4D
  - Multipass IFSAR

What's next - II

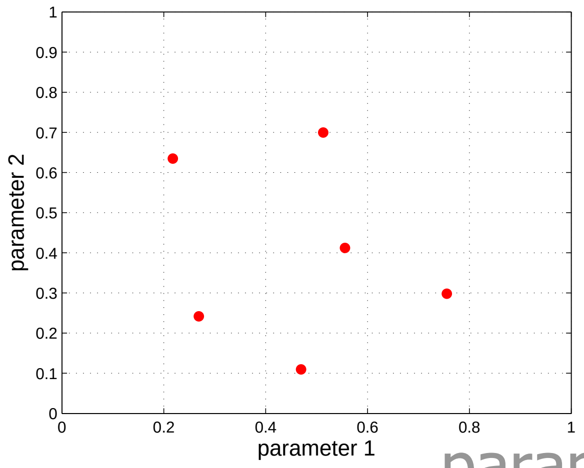
- Radar sensor degrees of freedom for unambiguous signal representation

True Shape	Best-fit Confuser Shapes: Monostatic Linear	Monostatic Nonlinear	Bistatic Nonlinear
Plate	~~dihedral~~ ~~cylinder~~		
Dihedral	~~plate~~ ~~cylinder~~	~~plate~~ ~~cylinder~~	~~plate~~
Trihedral			plate, ~~dih~~, ~~cyl~~, ~~top-hat~~
Cylinder	~~plate~~ ~~dihedral~~	~~plate~~ ~~dihedral~~	~~dihedral~~ ~~trihedral~~
Top-hat	~~plate~~, dih., ~~trih.~~, ~~cyl.~~, ~~sphere~~	dihedral, ~~cylinder~~, ~~sphere~~	~~plate~~, ~~dihedral~~, ~~trihedral~~
Sphere	~~dihedral~~ ~~cylinder~~		~~dihedral~~, ~~top-hat~~

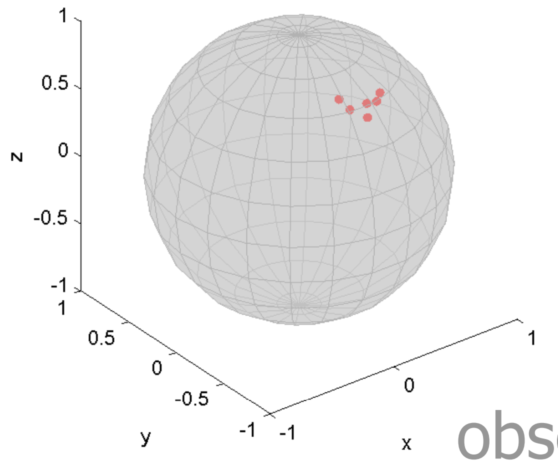
Polarization inconsistency   RCS inconsistency

What's next - III

- Regularized linear inversion for nonlinear regression problems
  - Unifying parametric and nonparametric processing techniques



parameters



observations