MITSUBISHI ELECTRIC
Changes for the Better

for a greener tomorrow

The Computational Sensing Revolution in Array Processing

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Mitsubishi Electric Corporation

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Changes for the Better

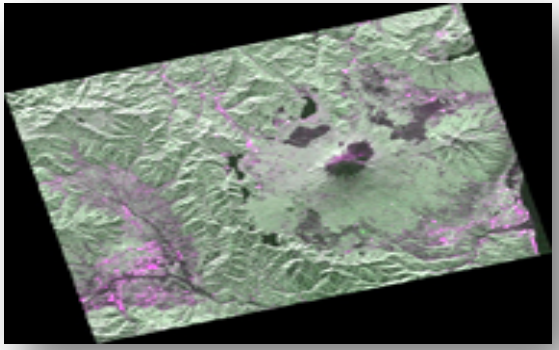
Automotive Equipment

Factory Automation Systems

Space Systems

Autonomous Driving & In-Vehicle Infotainment

Collaborative Robots for Production



Observation Satellites Remote Sensing

Other Key Business Areas ($45B annual revenue)

- Home (air conditioners)
- Transportation (train equipment)
- Building (elevators and escalators, surveillance, access control)
- Public/energy systems (plant monitoring, power transmission/distribution)

Corporate R&D Centers: Japan, Europe (UK & France), USA (MERL)

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MERL Profile & Technology Areas

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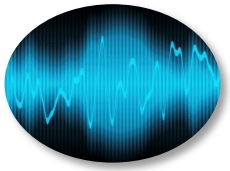
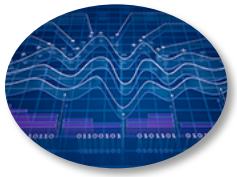
Computer Vision
Visual Analysis
3D Reconstruction & Processing
Simulation & Learning

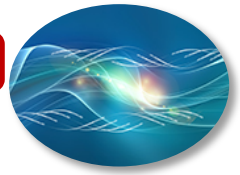
Speech & Audio
Speech Recognition
Audio Signal Processing
Natural Language Processing





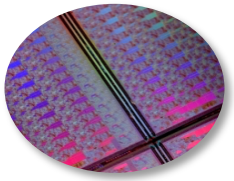
Data Analytics
Anomaly Detection
Predictive Modeling
Decision Optimization

Signal Processing
Computational Sensing
Wireless Communications
Optical Communications



Control & Dynamics
Control Algorithms
Nonlinear Dynamical Systems

Multi-Physical Systems
Electronic Devices
Modelling & Simulation



One of the most academically-oriented and open industrial research labs in the world

Engaged in mid/long-term research in areas that would be beneficial to parent company

60+ researchers in AI, signal processing, optimization and control, incl. 4 IEEE Fellows
→ http://www.merl.com/people
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We publish everything we do in leading conferences and journals (~200 pubs/year)
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More than 25 years of innovation!

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Computational Sensing @ MERL

Petros Boufounos

Dehong Liu

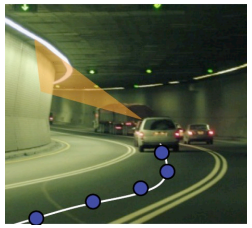
Hassan Mansour

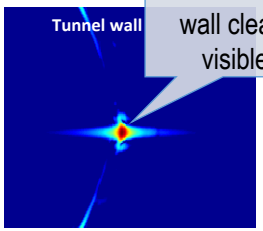
Perry Wang

Yanting Ma

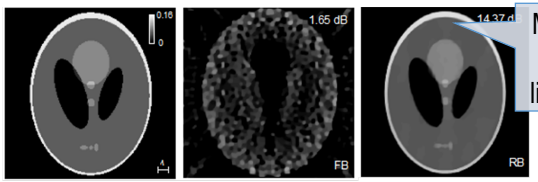
Material Sensing

Infrastructure Monitoring
Realize benefits of radar array for rapid infrastructure monitoring





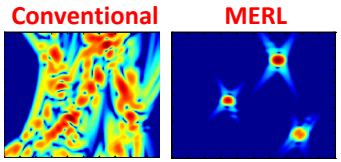
Defect within wall clearly visible.



Original Object | Linear Model (Reference) | Non-Linear Model (Proposed)

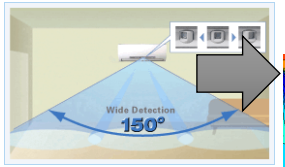
MERL method outperforms linear methods

Sparse reconstruction and EM modeling
Computationally efficient non-linear propagation model. Estimation of object permittivity based on reflected waves

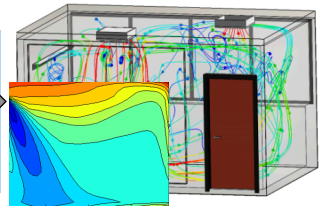


Distributed Sensing
Coherent integration of multiple sensors to improve SNR with large position errors

Airflow Sensing



Current: i-see sensor to monitor floor/wall temperature

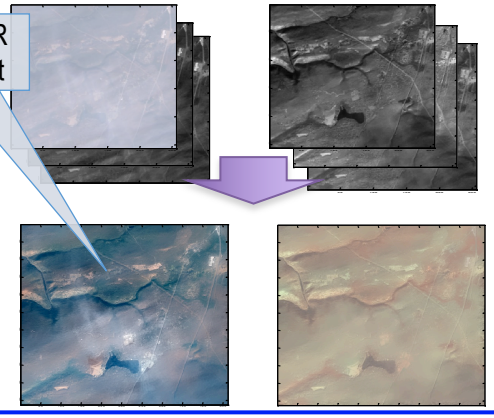


Target: dense 3D maps of temperature and airflow

Flow-sensor development: combined with fluid dynamical modeling and control to improve HVAC efficiency and user comfort

Multi-Band Image Fusion

1-2 dB PSNR improvement



Learning-Based Multispectral image super resolution: combing low quality RGB, Near/Short wave Infra-Red images to improve image quality and remove haze and clouds

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THE BIG PICTURE

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Computational Sensing Reveolution

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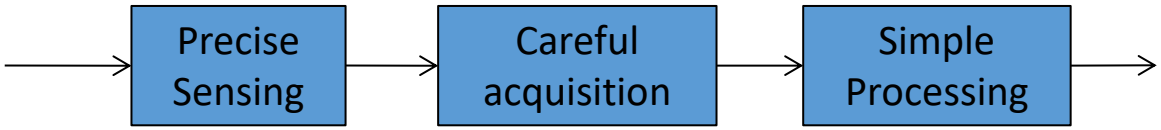
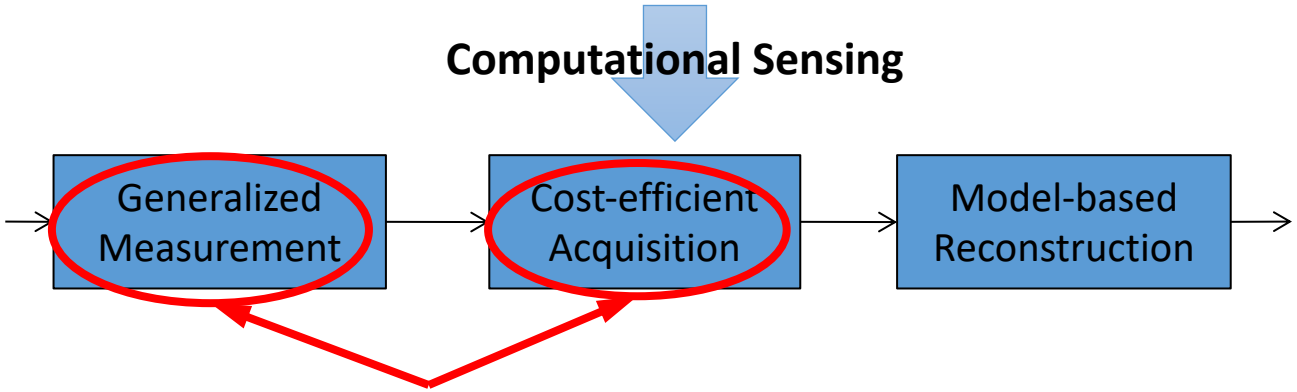
Conventional Sensing Pipeline



Sensor designed to collect as pristine information as possible
(linear, high dynamic range, high precision, high sampling rate etc.)
Processing is simple because the data is very “clean” and well-measured

Computational Sensing



Goal: exploit mixing to **simplify sensor or improve sensor** specifications (e.g., sensor speed, A/D conversion rate, measured bandwidth/resolution)

Reconstruction methods can guide sensor development and vice versa

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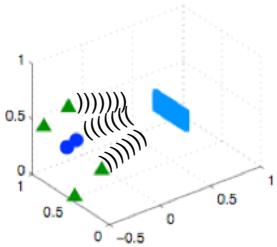
Today

Computational Sensing Principles

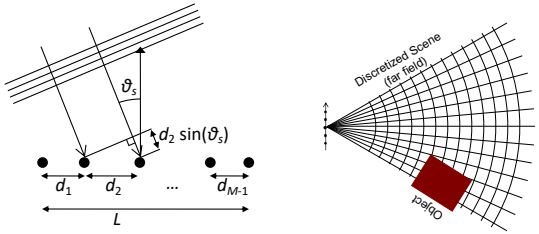


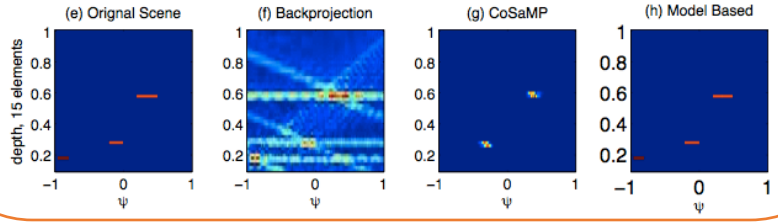
$$y_l(t) = x_n p_s(t - \tau_{s,l,n})$$
$$\Longleftrightarrow$$
$$Y_{l,f} = x_n P_{s,f} e^{-j\omega_f \tau_{s,l,n}}$$

$$\underbrace{\mathbf{y}}_{\text{Received data}} = \underbrace{\mathbf{A}}_{\substack{\text{Sensing Matrix} \\ \text{(determined by system design)}}} \underbrace{\mathbf{x}}_{\substack{\text{Scene} \\ \text{(unknown)}}}$$

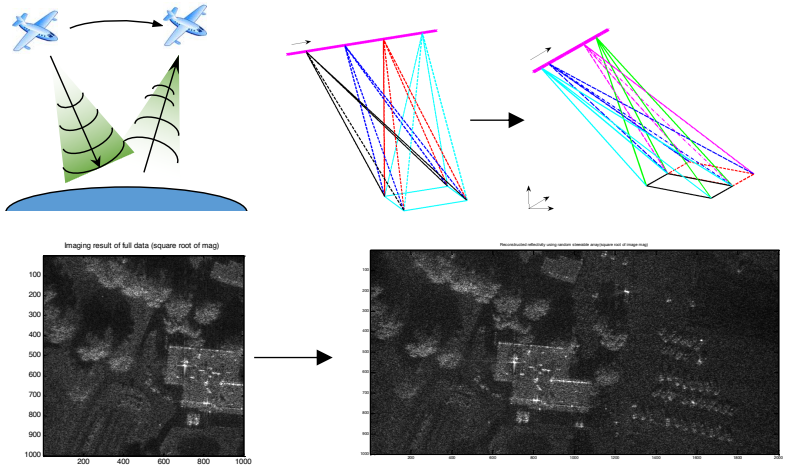
$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda R(\mathbf{x})$$

Radar and Array Processing

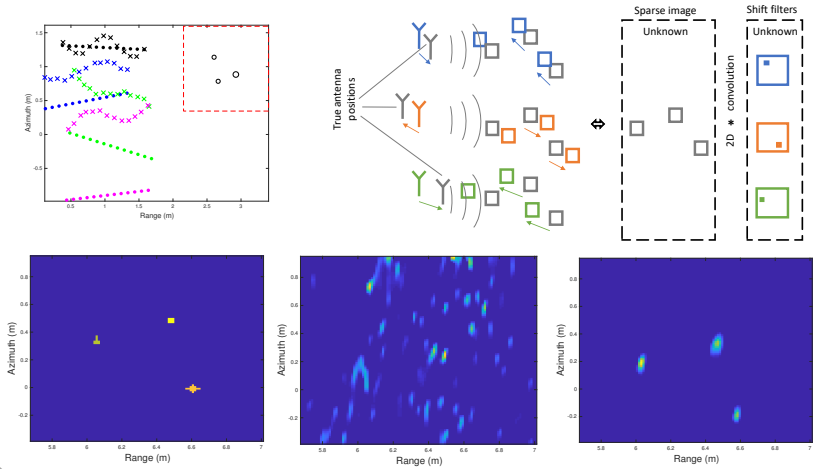




Synthetic Aperture Radar



Distributed Array Processing



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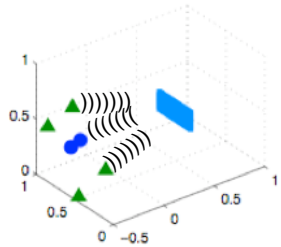
Today

Computational Sensing Principles



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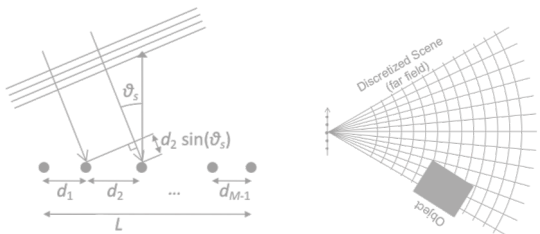
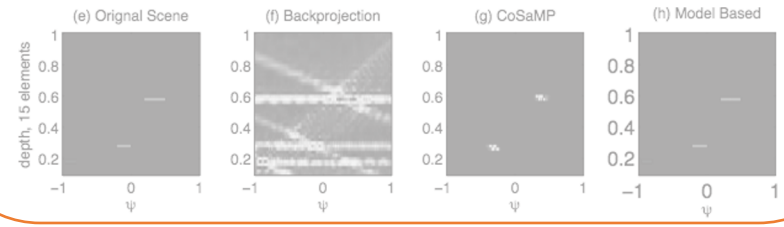
Radar and Array Processing





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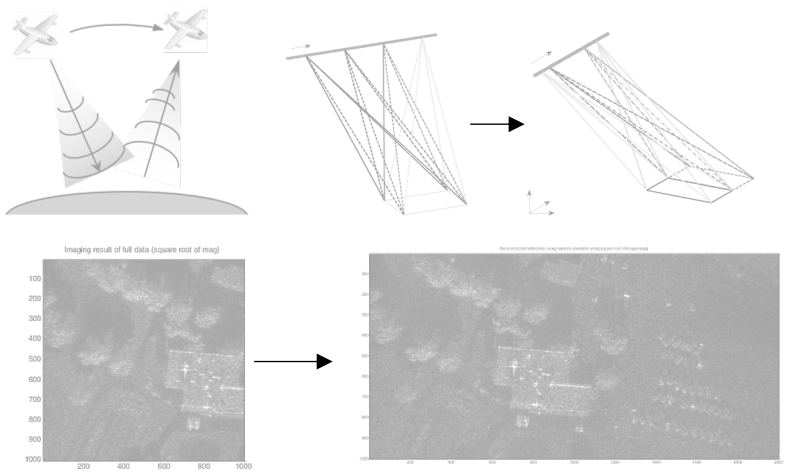
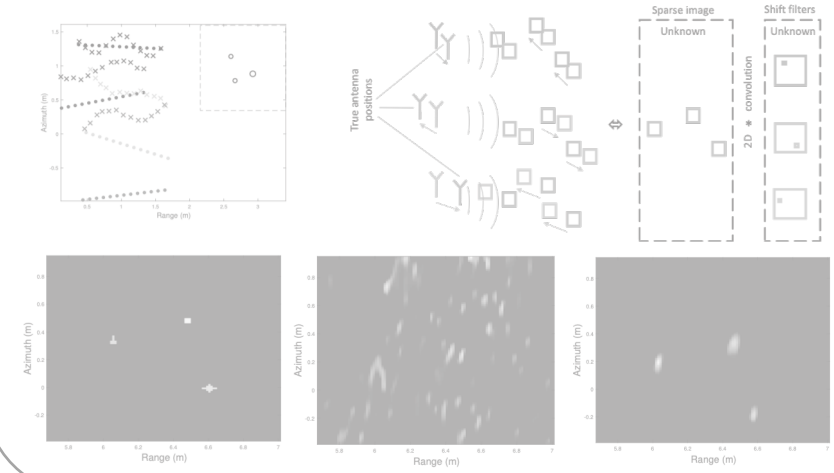


Distributed Array Processing



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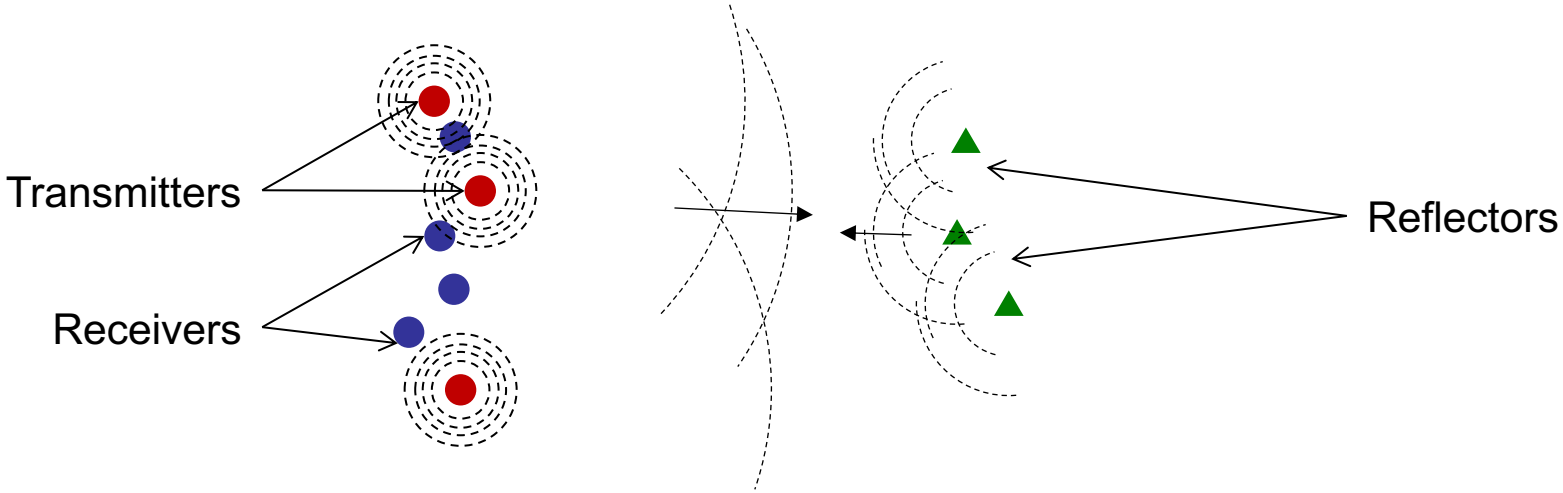
(Active) Array Processing Problem



Transmitters illuminate the scene

Reflectors reflect incident waves

Receivers receive the reflections

Can we localize/reconstruct/image sources in the scene?

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SYSTEM MODELING

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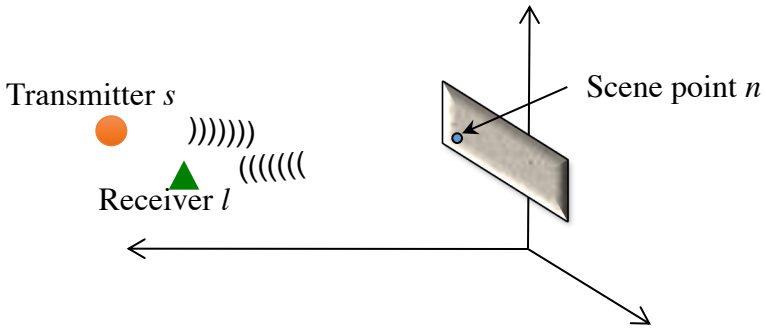
Propagation Model



Reflectivity of scene point n (signal of interest):	x_n
Pulse transmitted by transmitter s (freq. domain):	$P_{s,f}$
Signal received by receiver l (freq. domain):	$Y_{l,f}$
Distance of transmitter s to scene point n:	$d_{s,n}$
Distance of receiver l to scene point n:	$d_{n,l}$
Speed of propagation:	c
Time delay for distance d:	d/c
Time delay from s to l through n:	$\tau_{s,l,n}=(d_{s,n}+d_{n,l})/c$

S transmitters, L receivers, N scene points (scene discretized), F transmitted frequencies

$$y_l(t) = x_n p_s(t - \tau_{s,l,n})$$

$$\Longleftrightarrow$$

$$Y_{l,f} = x_n P_{s,f} e^{-j\omega_f \tau_{s,l,n}}$$

Propagation Delay

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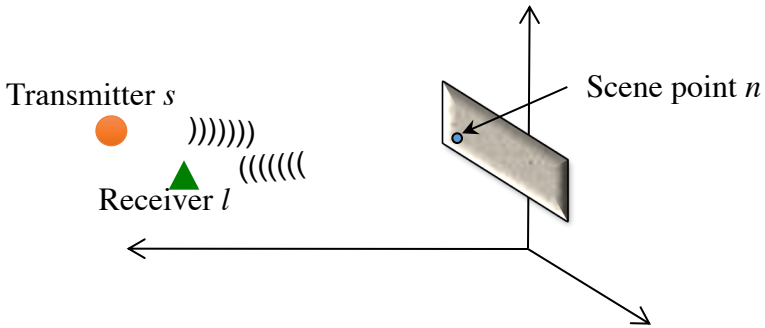
System Model



Reflectivity of scene point n (signal of interest):	x_n
Pulse transmitted by transmitter s (freq. domain):	$P_{s,f}$
Signal received by receiver l (freq. domain):	$R_{l,f}$
Distance of transmitter s to scene point n:	$d_{s,n}$
Distance of receiver l to scene point n:	$d_{n,l}$
Speed of propagation:	c
Time delay for distance d:	d/c
Time delay from s to l through n:	$\tau_{s,l,n}=(d_{s,n}+d_{n,l})/c$

S transmitters, L receivers, N scene points (scene discretized), F transmitted frequencies

Propagation equation: $$Y_{l,f} = x_n P_{s,f} e^{-j\omega_f \tau_{s,l,n}}$$

Discretizing in Frequency and converting to matrix form:

$$\mathbf{y} = \begin{bmatrix} Y_{1,1} \\ \vdots \\ Y_{1,F} \\ \vdots \\ Y_{l,f} \\ \vdots \\ Y_{L,1} \\ \vdots \\ Y_{L,F} \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} \sum_s P_{s,1} e^{-j\omega_1 \tau_{s,1,1}} & \cdots & \sum_s P_{s,1} e^{-j\omega_1 \tau_{s,1,N}} \\ \vdots & \ddots & \vdots \\ \sum_s P_{s,F} e^{-j\omega_F \tau_{s,1,1}} & \cdots & \sum_s P_{s,F} e^{-j\omega_F \tau_{s,1,N}} \\ \vdots & \ddots & \vdots \\ \sum_s P_{s,f} e^{-j\omega_f \tau_{s,l,1}} & \cdots & \sum_s P_{s,f} e^{-j\omega_f \tau_{s,l,N}} \\ \vdots & \ddots & \vdots \\ \sum_s P_{s,1} e^{-j\omega_1 \tau_{s,L,1}} & \cdots & \sum_s P_{s,1} e^{-j\omega_1 \tau_{s,L,N}} \\ \vdots & \ddots & \vdots \\ \sum_s P_{s,F} e^{-j\omega_F \tau_{s,L,1}} & \cdots & \sum_s P_{s,F} e^{-j\omega_F \tau_{s,L,N}} \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix}$$

$$\omega_f = \frac{2\pi f}{F}$$

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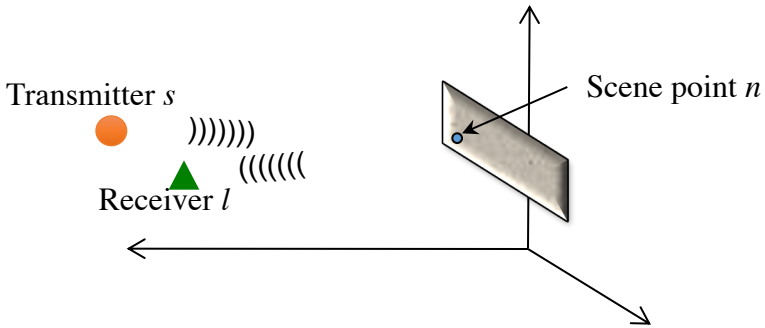
System Model



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Speed of propagation:	c
Time delay for distance d:	d/c
Time delay from s to l through n:	$\tau_{s,l,n}=(d_{s,n}+d_{n,l})/c$

S transmitters, L receivers, N scene points (scene discretized), F transmitted frequencies

$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data

Sensing Matrix
(determined by system design)

Scene
(unknown)

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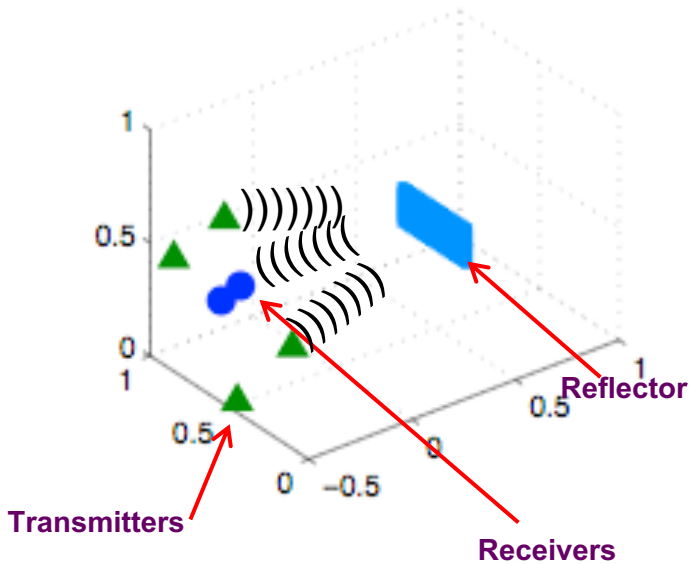
Scene Model

$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data

Sensing Matrix

Scene



Scene Reflectivity
(at every point in the scene)

Typical scenarios: very few reflectors in scene

Often reflectors are not permeable
(can't see behind them)

Scene is sparse!
(i.e., mostly zeros)

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ACQUISITION AND RECOVERY

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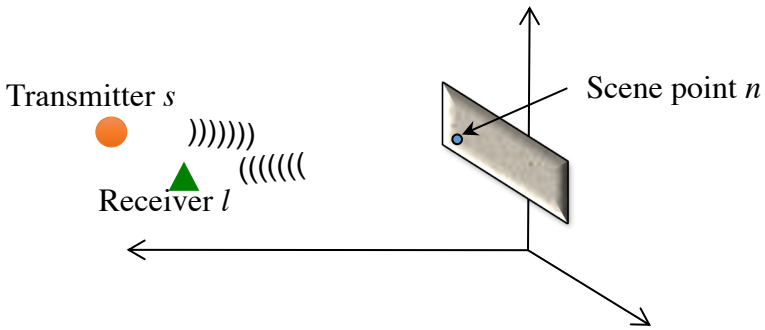
Acquisition and Recovery



$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data

Sensing Matrix (determined by pulsing method)

Scene (sparse)

Problem 1 - Recovery: Given $\mathbf{y}$, what is $\mathbf{x}$?

(most of the discussion today)

$$\widehat{\mathbf{x}} = \text{“}\mathbf{A}^{-1}\text{”}\mathbf{y}$$

Problem 2 - Design: How to get a good $\mathbf{A}$?

(just a bit on that today)

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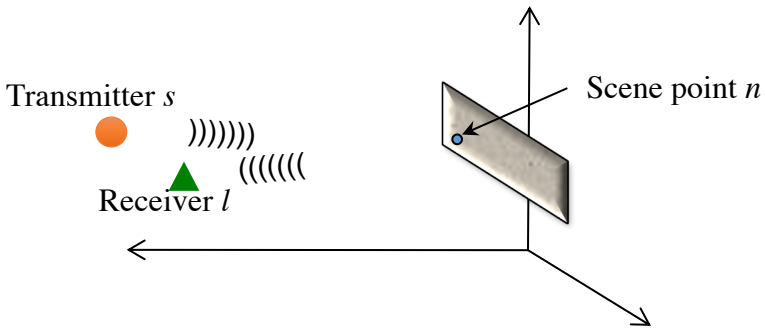
Simple Computation: Least Squares Inversion



$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data

Sensing Matrix (determined by pulsing method)

Scene (sparse)

Problem 1 - Recovery: Given $\mathbf{y}$, what is $\mathbf{x}$?

Least Squares Inversion:

$$\hat{\mathbf{x}} = \mathbf{A}^{\dagger}\mathbf{y}$$

In fact two different approaches:

Least norm solution if underdetermined system:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_2 \text{ s.t. } \mathbf{x} = \mathbf{A}\mathbf{y}$$

Least squares fit if overdetermined system:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2$$

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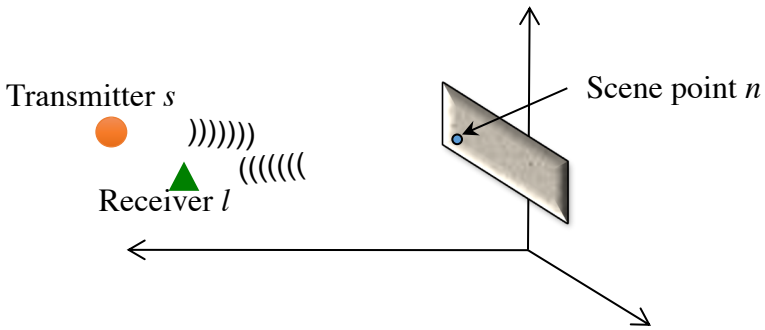
Simple Computation: Matched Filter



$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data

Sensing Matrix (determined by pulsing method)

Scene (sparse)

Problem 1 - Recovery: Given $\mathbf{y}$, what is $\mathbf{x}$?

Least Squares Inversion:

$$\hat{\mathbf{x}} = \mathbf{A}^{\dagger}\mathbf{y}$$

Matched Filter:
(a.k.a., backprojection,
delay and sum beamforming, etc.)

$$\hat{\mathbf{x}} = \mathbf{A}^{*}\mathbf{y}$$

Performs well in practice, as long as $\mathbf{A}$ is "well behaved" (low sidelobes, no grating lobes, etc.)

Drawback: none of these methods take a model for $\mathbf{x}$ into account (remember, **scene is sparse!**)

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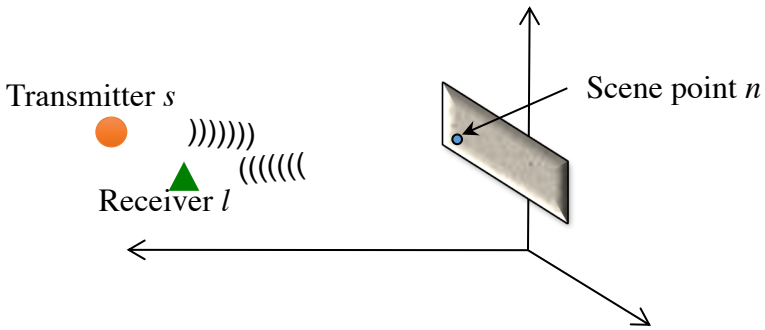
Sparse/Model Based Inversion



$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data

Sensing Matrix (determined by pulsing method)

Scene (sparse)

Problem 1 - Recovery: Given $\mathbf{y}$, what is $\mathbf{x}$?

General Inverse Problem Principles

Find $\mathbf{x}$, such that $\mathbf{y} \approx \mathbf{A}\mathbf{x}$ and fits the model

$$\widehat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda R(\mathbf{x})$$

(sparsity)

$$\widehat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda \|\mathbf{x}\|_1$$

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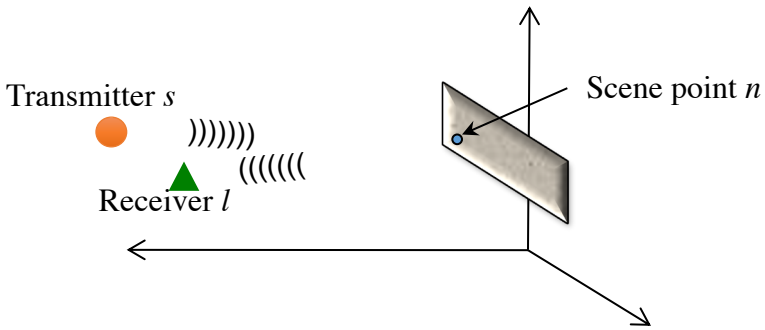
Sparse/Model Based Inversion



$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data

Sensing Matrix (determined by pulsing method)

Scene (sparse)

Problem 1 - Recovery: Given $\mathbf{y}$, what is $\mathbf{x}$?

Sparse Recovery Problem

$$\widehat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda\|\mathbf{x}\|_1$$

General Idea: Find the **sparsest signal** that **explains the data**

Computation is a significant component!

We have many efficient ways to compute the solution, or approximations to it (convex optimization, greedy approximations, fast first-order algorithms)

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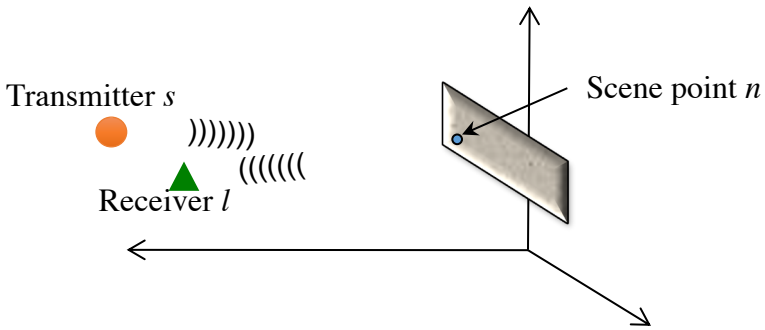
Sensing and Pulsing



$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data

Sensing Matrix (determined by pulsing method)

Scene (sparse)

Problem 2 - Design: How to get the best $\mathbf{A}$?

Pulse **Bandwidth** ⇔ Depth resolution
(but higher bandwidth requires higher sampling rate)

Array **Size** (aperture) ⇔ Angle (spatial) resolution
(but larger array requires more elements)

More elements simultaneously transmitting ⇒ more interference
(randomize/code pulses to be able to separate them)

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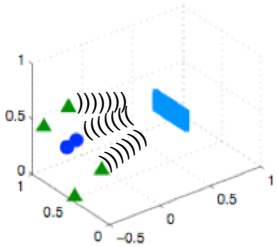
Today

Computational Sensing Principles



$$y_l(t) = x_n p_s(t - \tau_{s,l,n})$$
$$\Longleftrightarrow$$
$$Y_{l,f} = x_n P_{s,f} e^{-j\omega_f \tau_{s,l,n}}$$

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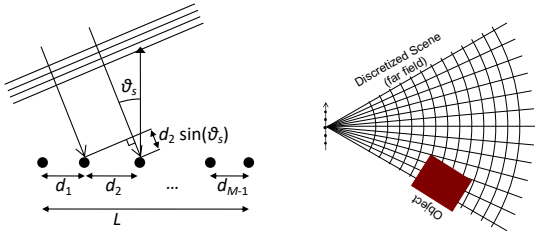
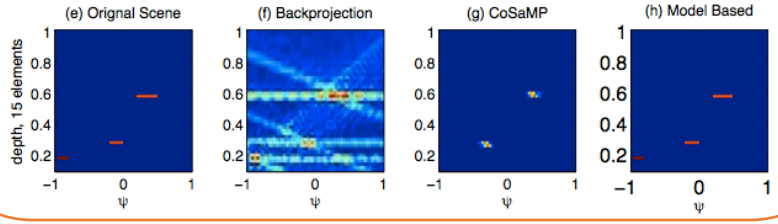
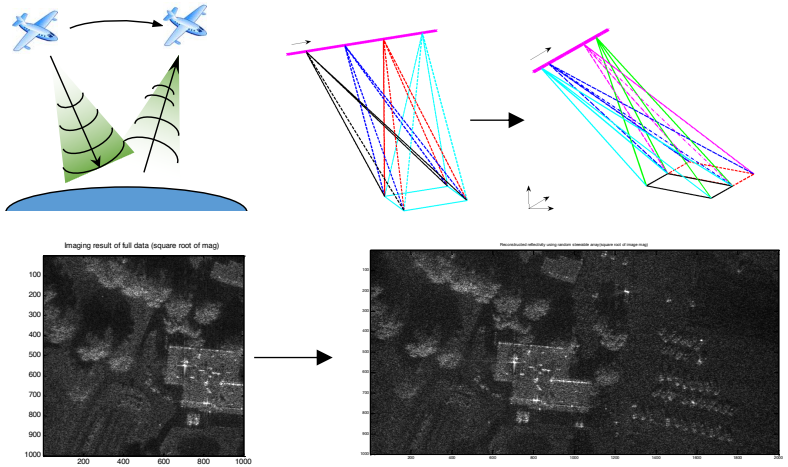
Radar and Array Processing

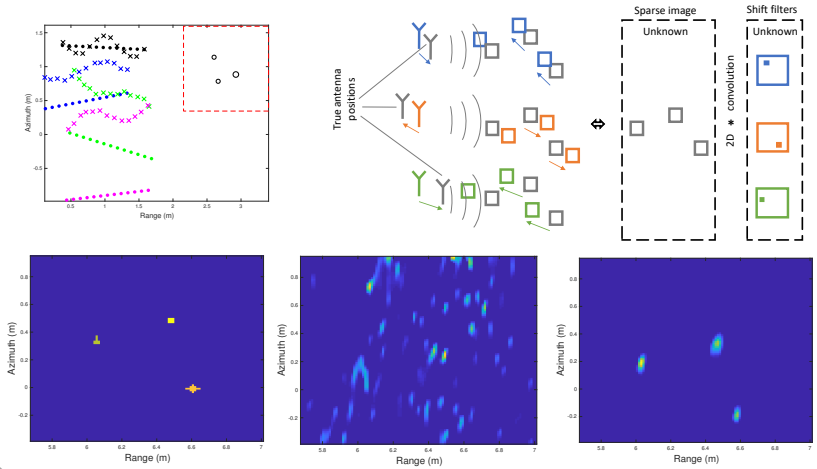




Synthetic Aperture Radar



Distributed Array Processing



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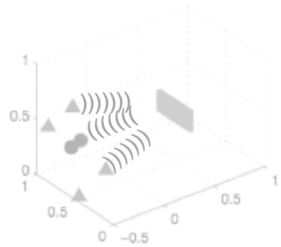
Today

Computational Sensing Principles



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$$\Longleftrightarrow$$

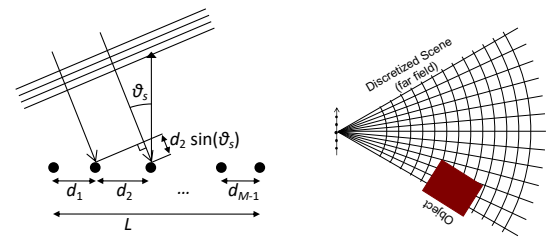
$$Y_{l,f} = x_n P_{s,f} e^{-j\omega_f \tau_{s,l,n}}$$

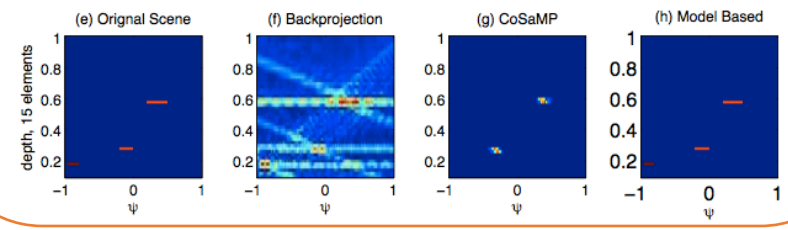
$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

Received data — Sensing Matrix (determined by system design) — Scene (unknown)

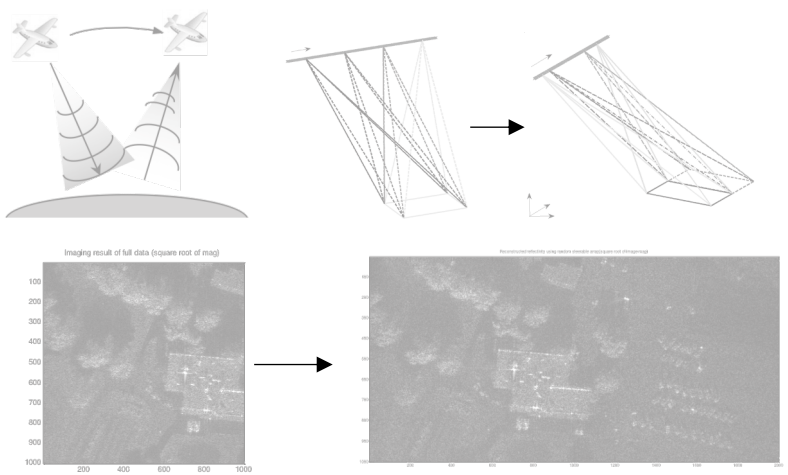
$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda R(\mathbf{x})$$

Radar and Array Processing

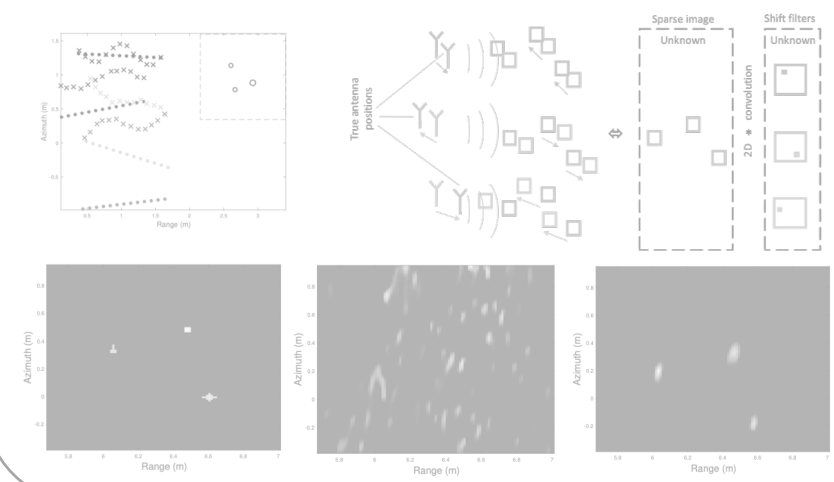




Synthetic Aperture Radar



Distributed Array Processing



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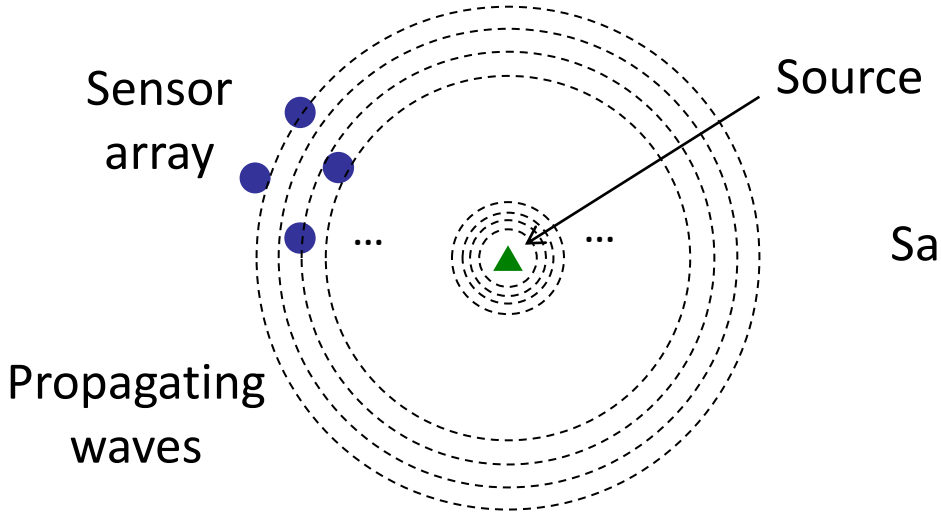
Wave Propagation, Far-field Approximation

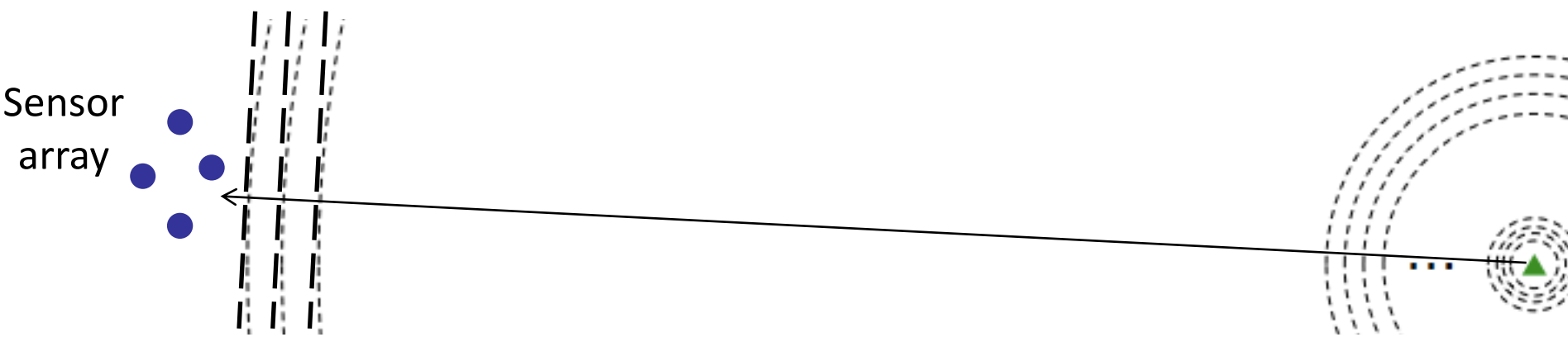


Propagating waves are circular:
Same delay for same distance from source

Far field approximation

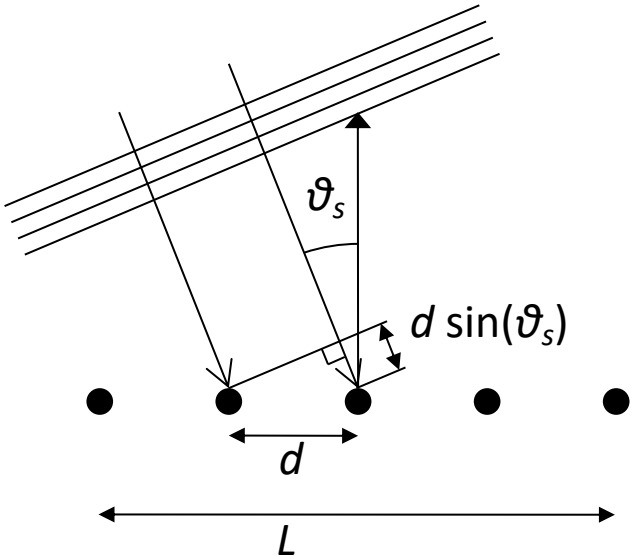
Sources located **far relative to array size**

Propagating waves become **flat (planar)**

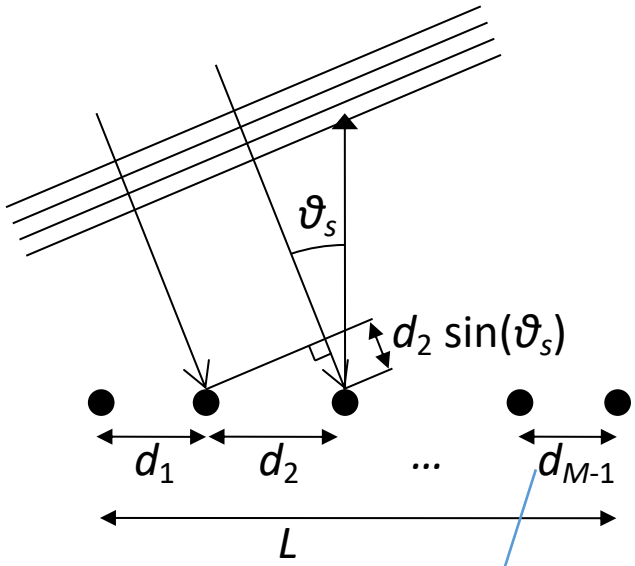


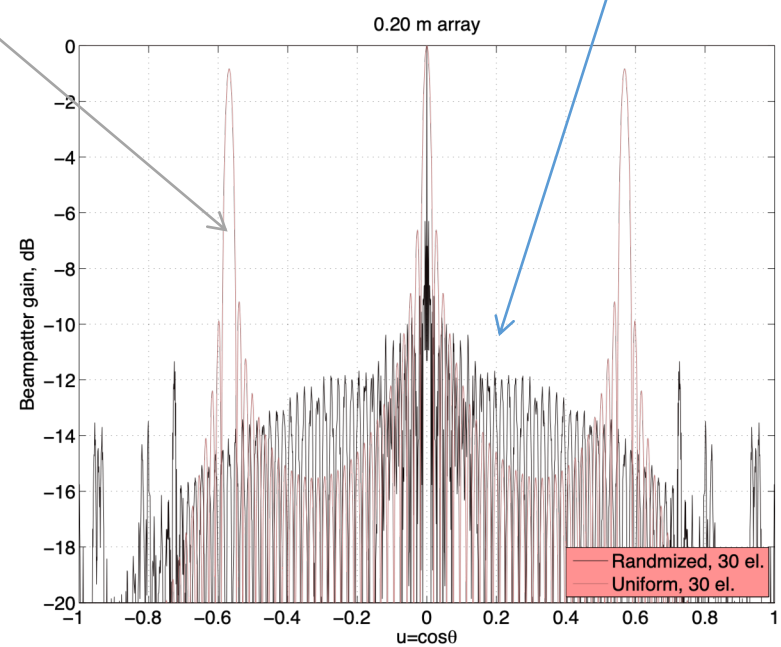
Array Design

Uniform Spacing



Non-Uniform Spacing





Array parameters

- Operating Frequency: 76-77GHz (λ/2≈2mm)
- Aperture size: 20cm
- Array Elements: 30 (instead of ~100)

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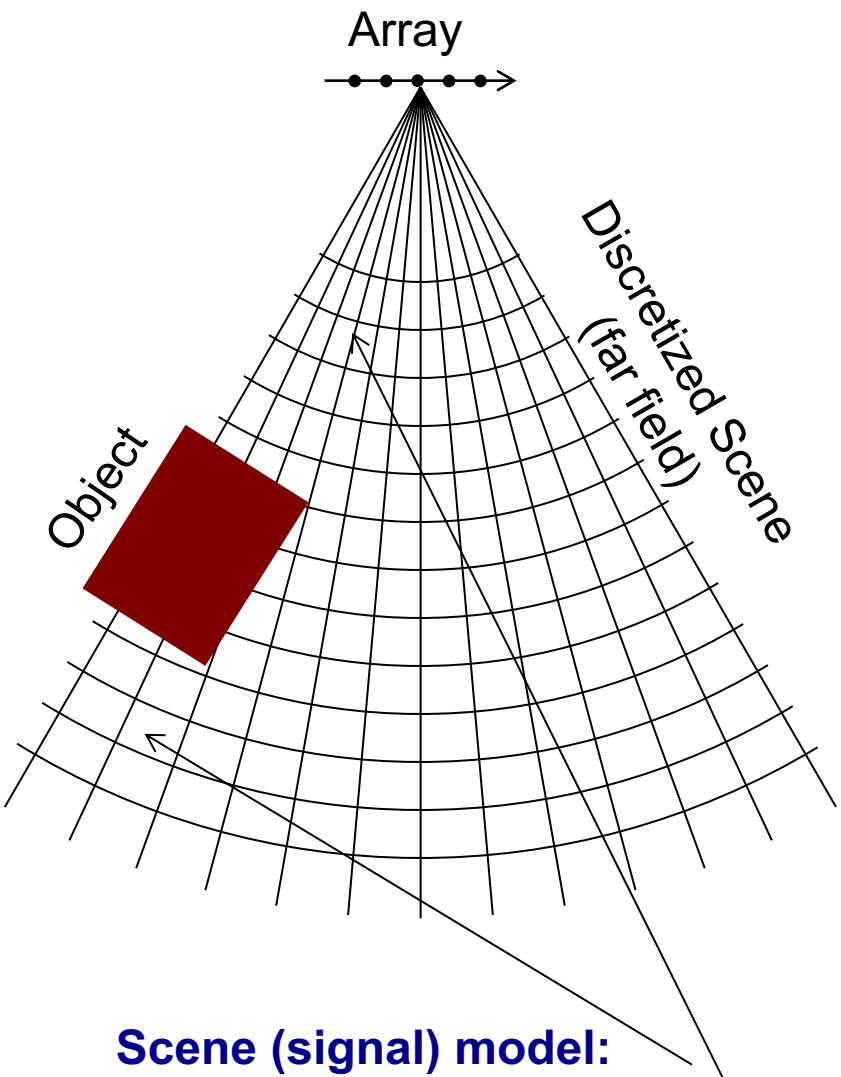
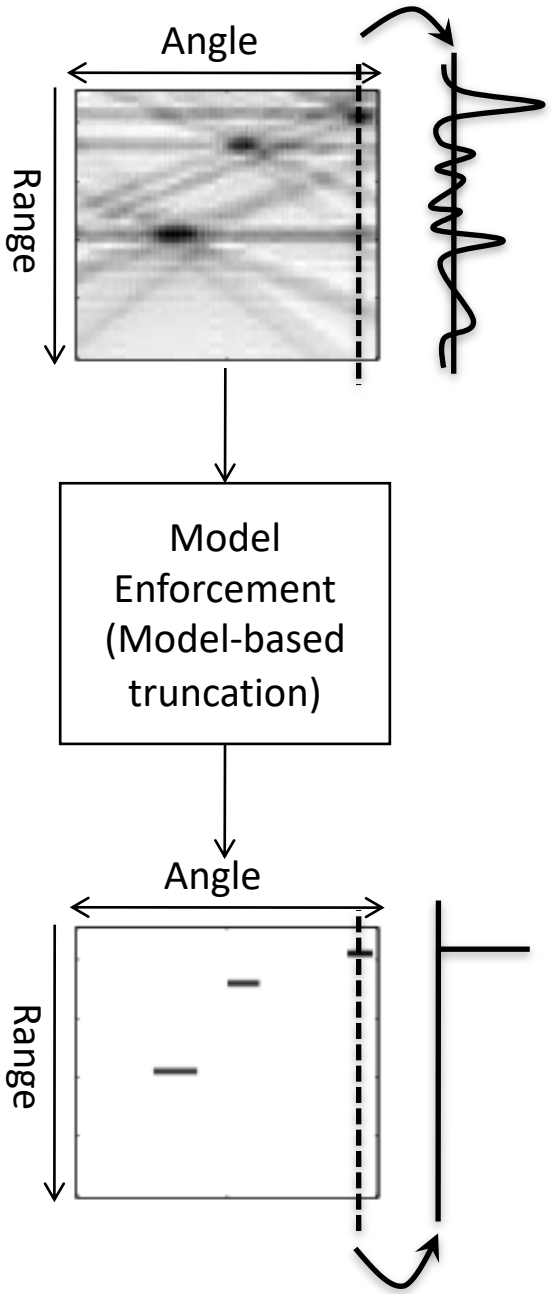
Radar Scene Model





Scene (signal) model:
Front of objects is empty (**zero**)
Rear of objects is invisible (**zero**)

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Example: mmWave Radar Simulation

- Operating Frequency: 76-77GHz

- Simulation in 2D-field (easier to visualize results)
  - Assuming uniform linear array

- Compared three approaches
  - Classical backprojection (beamforming)
  - Standard Compressive Sensing (CoSaMP)
  - Model-based Compressive Sensing

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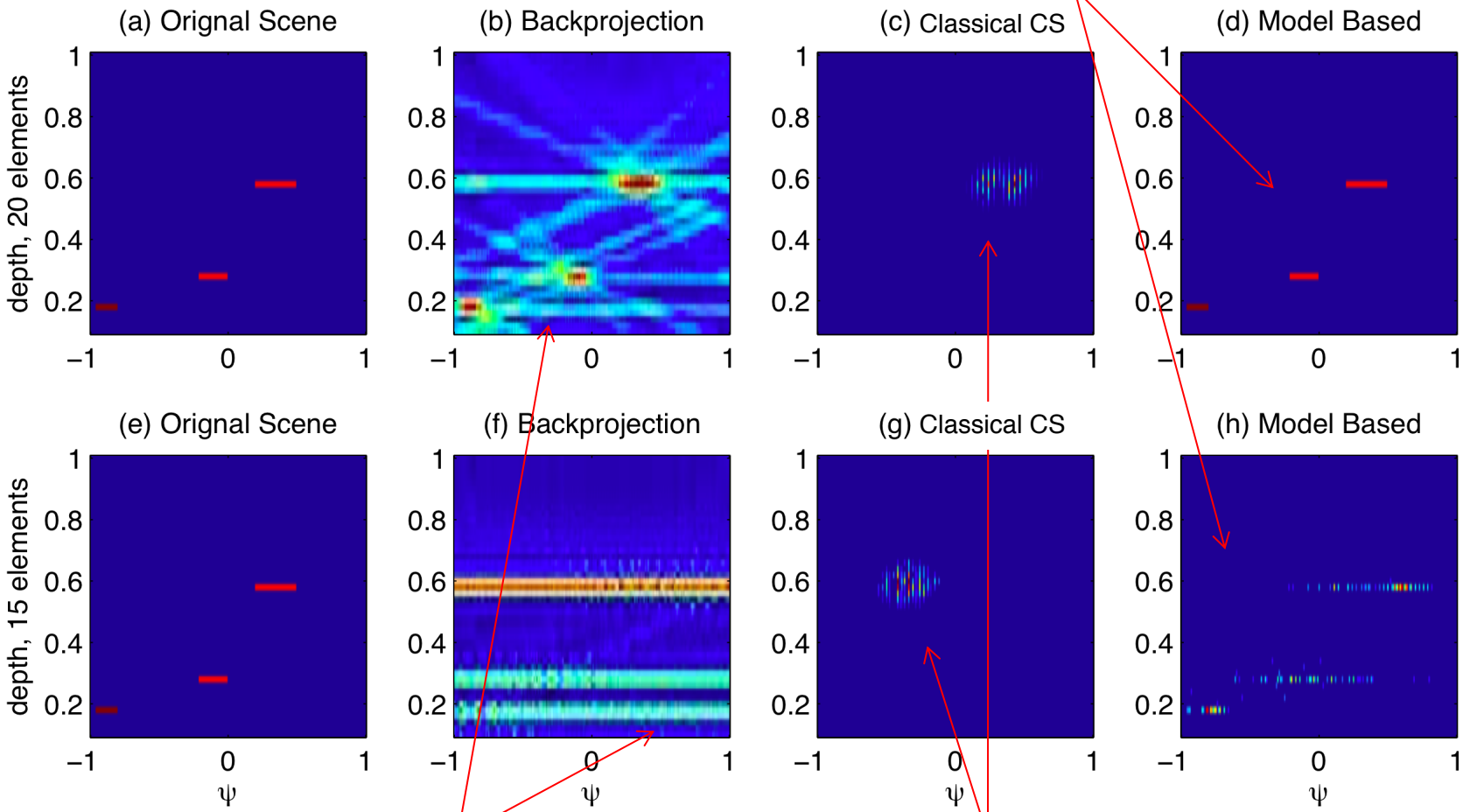
Example: Array with uniform spacing

Model enforcement improves reconstruction significantly, even with significant blur



Backprojection (beamforming) exhibits significant blur, especially as array elements are reduced

Blur also confuses Classical CS algorithms

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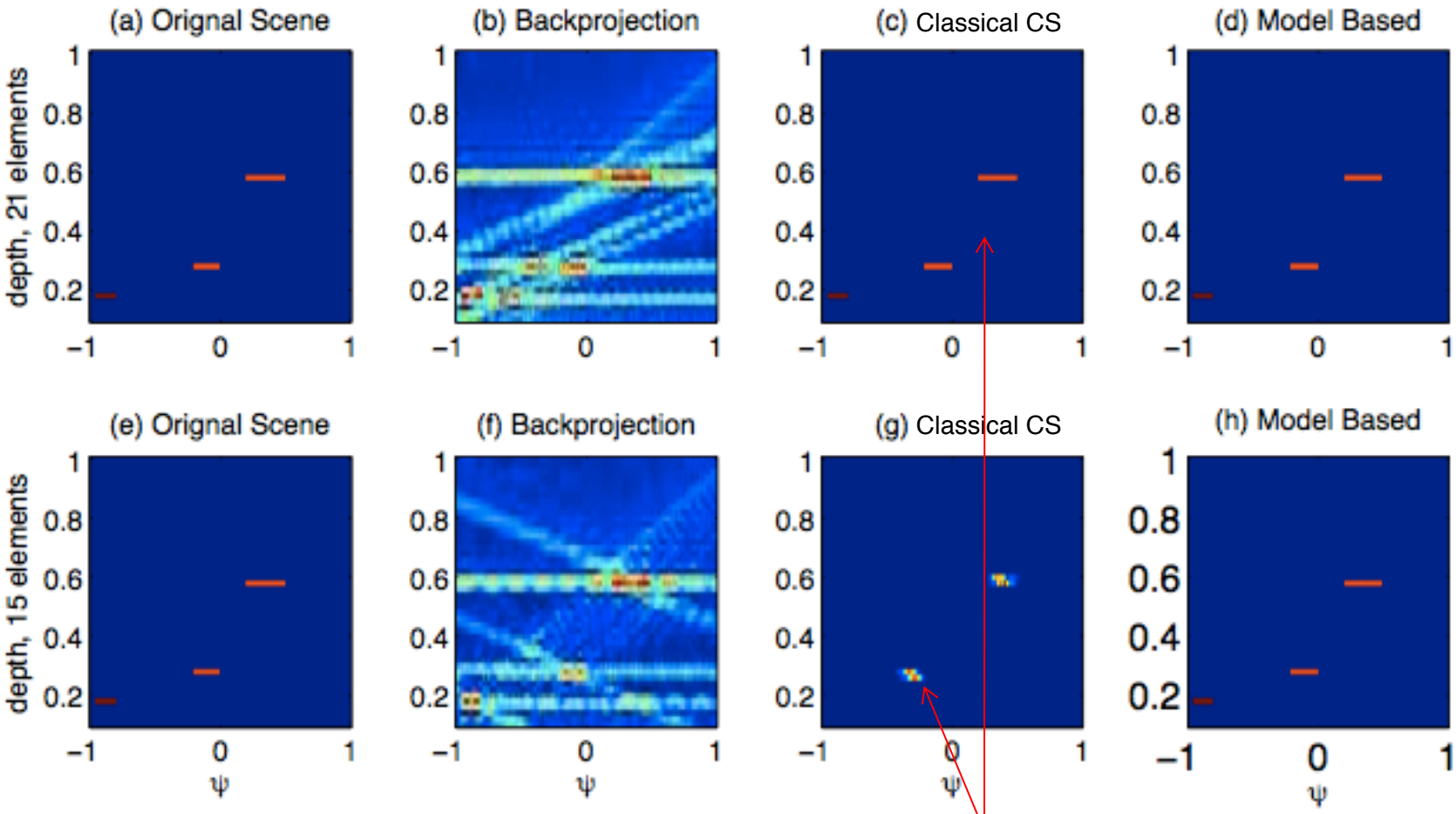
Example: Array with randomized spacing



Standard CS performance improves, but not perfect

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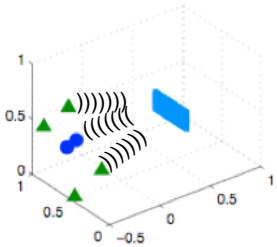
Today

Computational Sensing Principles



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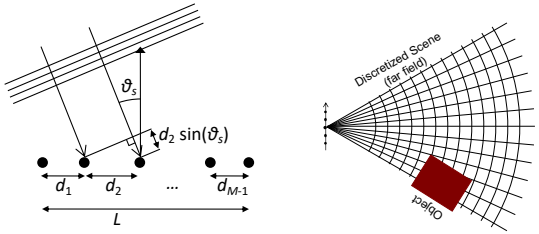
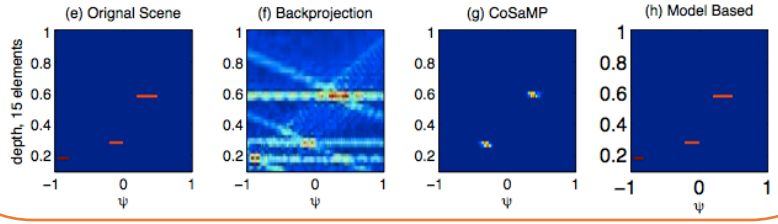
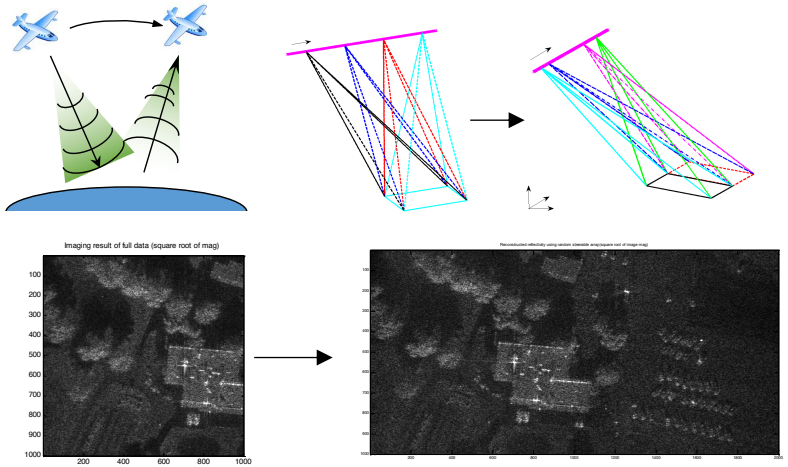
Radar and Array Processing

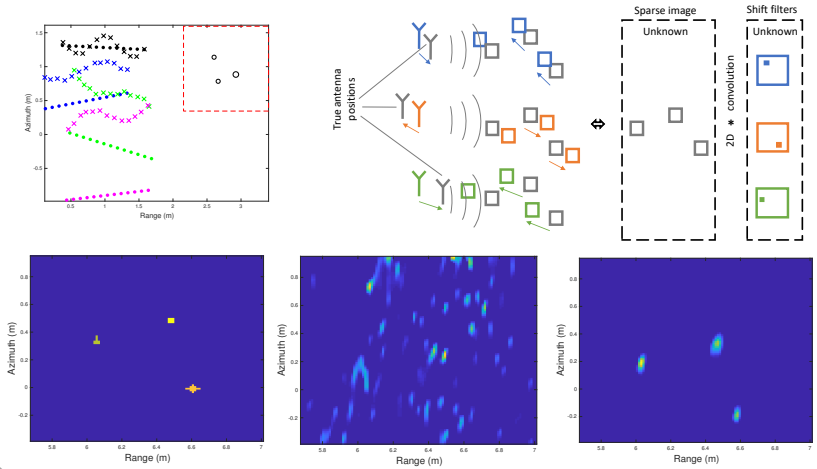




Synthetic Aperture Radar



Distributed Array Processing



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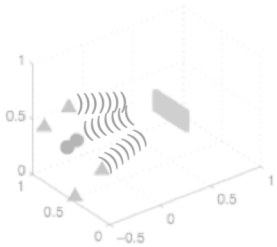
Today

Computational Sensing Principles



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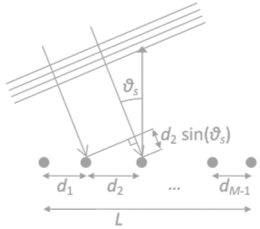
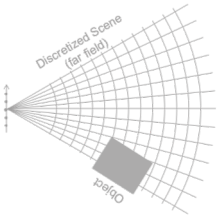
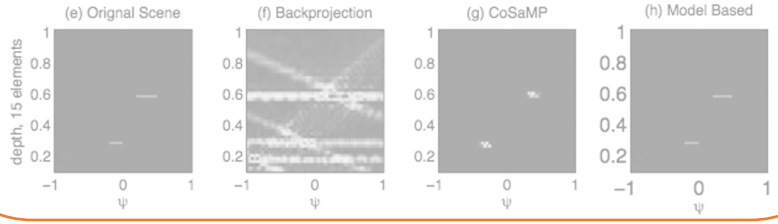
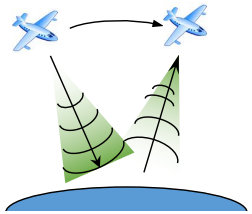
Radar and Array Processing

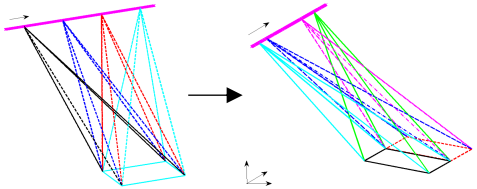


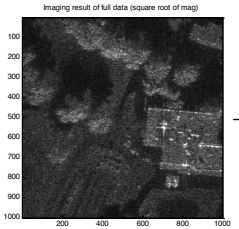


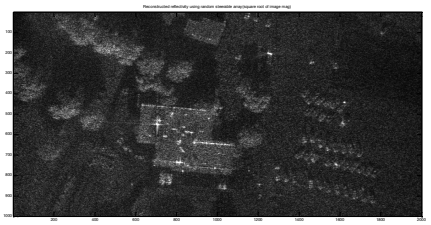


Synthetic Aperture Radar

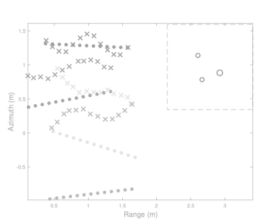


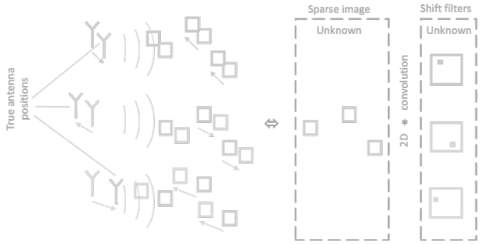


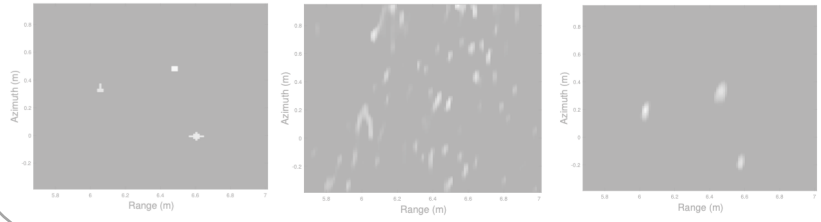




Distributed Array Processing







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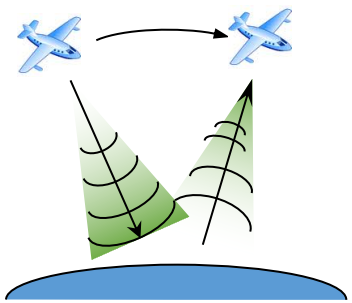
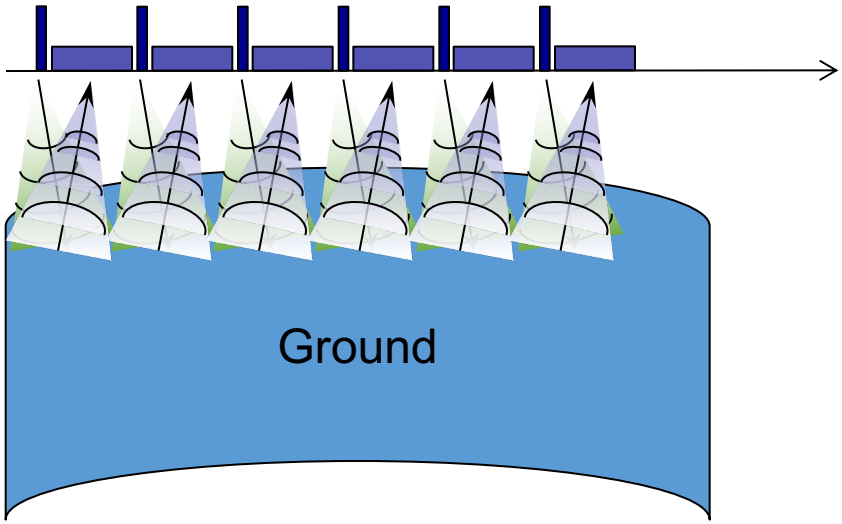
Synthetic Aperture Radar (SAR)



Received Data: $\mathbf{y}$

Ground Image: $\mathbf{x}$



SAR Acquisition Linear Equation: $\mathbf{y} = \mathbf{A}\,\mathbf{x}$

- SAR Acquisition follows linear model
- Acquisition function ($\mathbf{A}$) determined by SAR parameters
  - Pulse shape/rate
  - Moving platform trajectory
- Image formation: given $\mathbf{y}$ determine $\mathbf{x}$.

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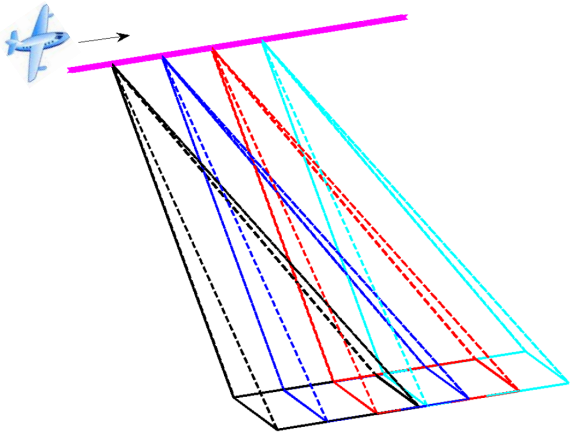
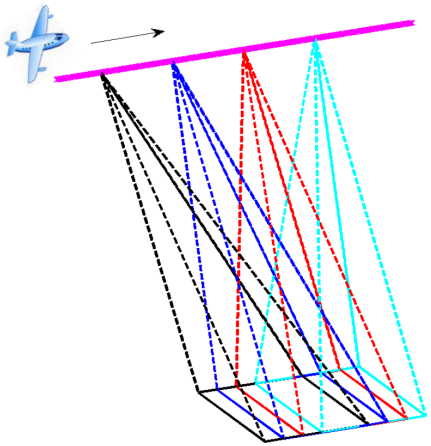
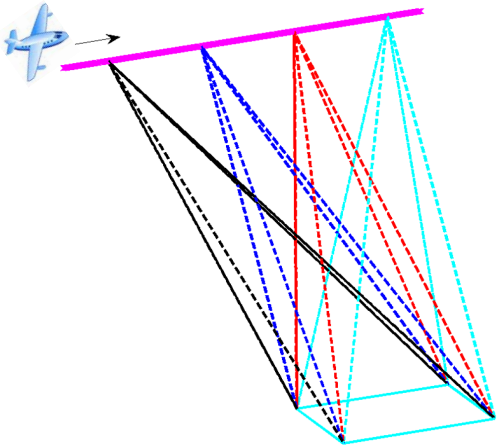
SAR Modes: Coverage vs. Resolution



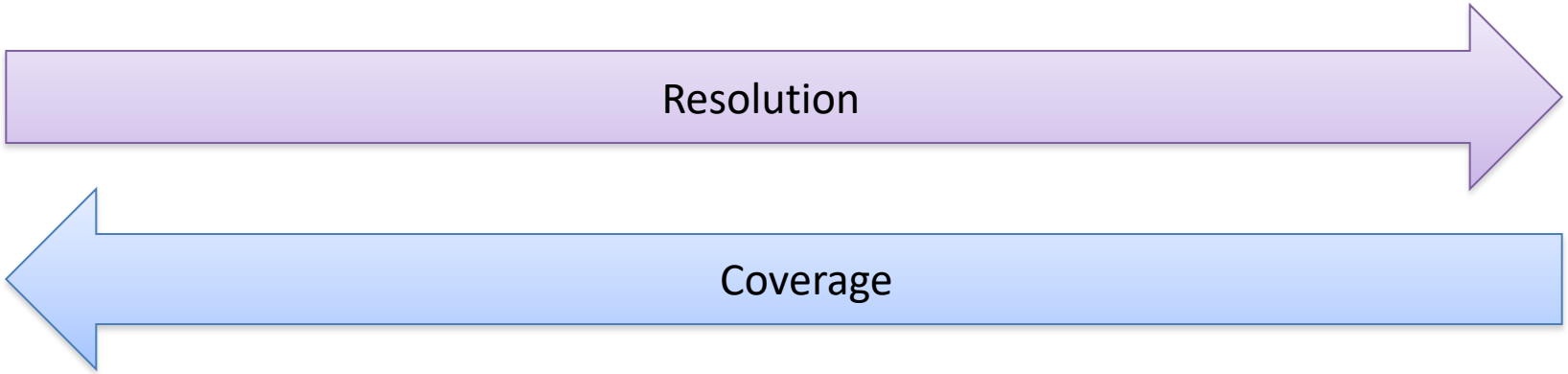
Strip-map mode
Beam not steered



Sliding mode
Beam Steered



Spotlight mode
Beam Steered



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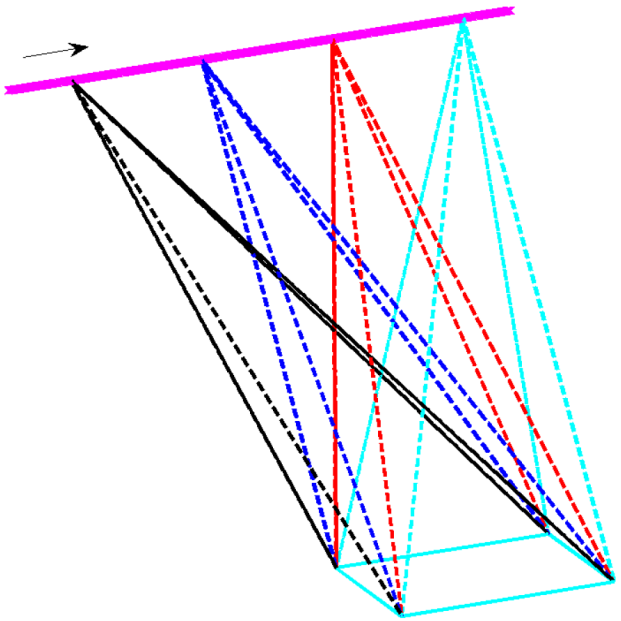
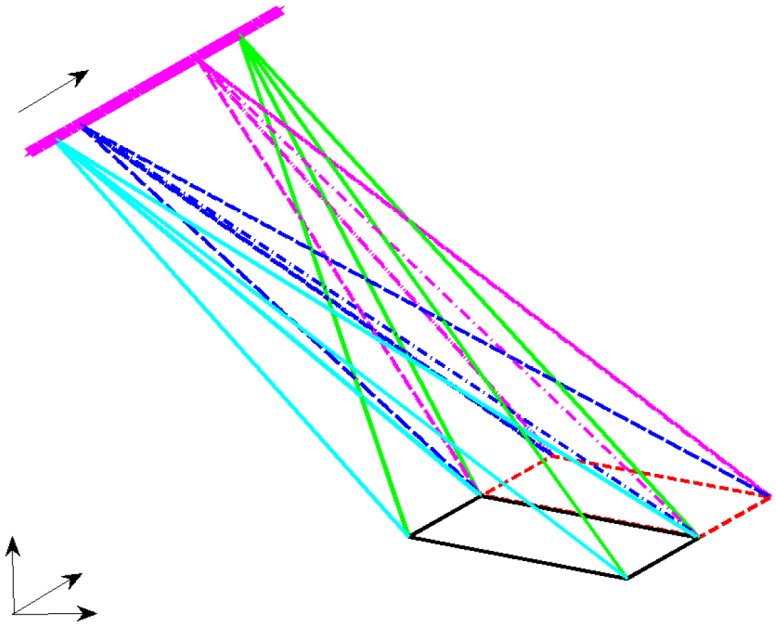
Spotlight Mode, Randomly Steerable



Classical spotlight mode



Randomly steerable mode

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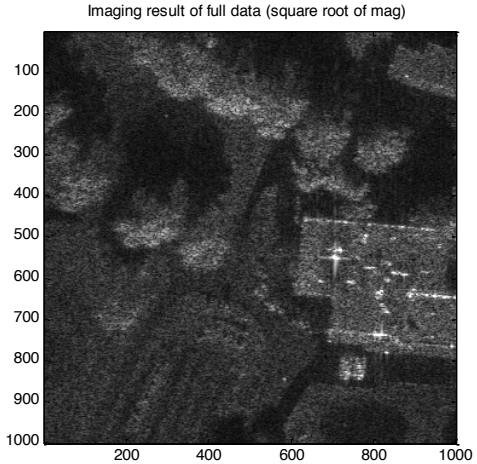
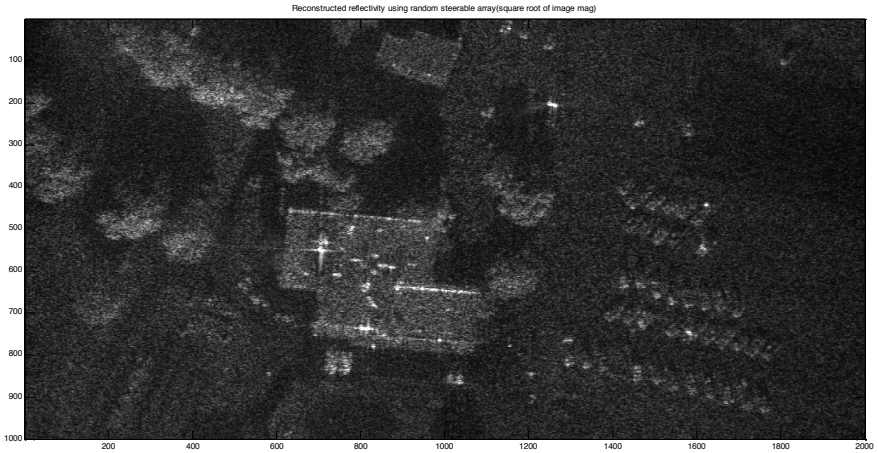
Conventional array vs. random steerable array

True reflectivity



Conventional spotlight array



Random steerable spotlight mode

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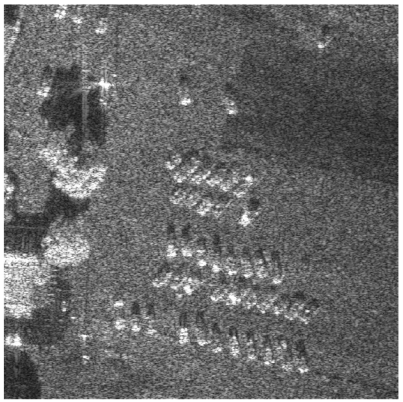
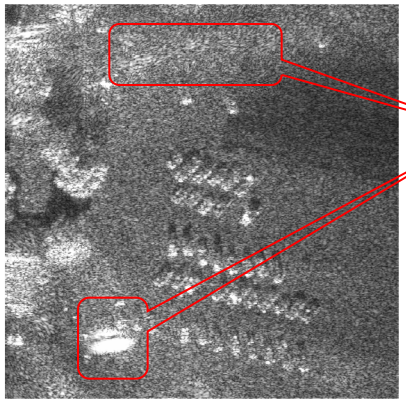
Reconstruction Results, Single Spot

Conventional spotlight mode



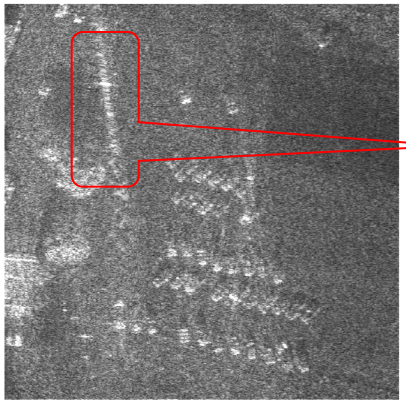
Conventional reconstruction, full data



Ghosting

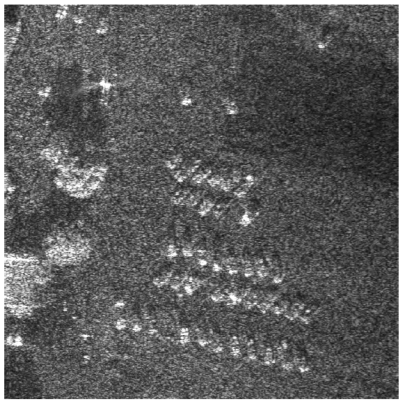
Conventional reconstruction, uniform downsampling

Random steerable array



Leakage from strong scatterers

Wavelet-sparsity reconstruction



Proposed method (spatial sparsity)

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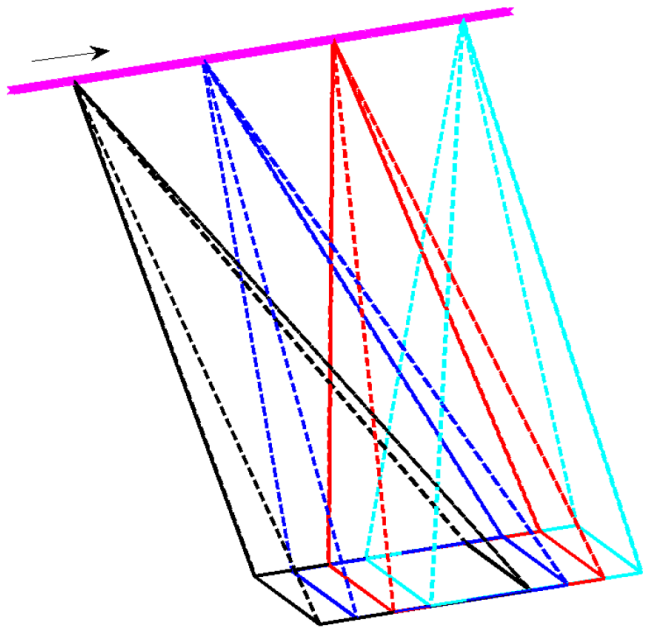
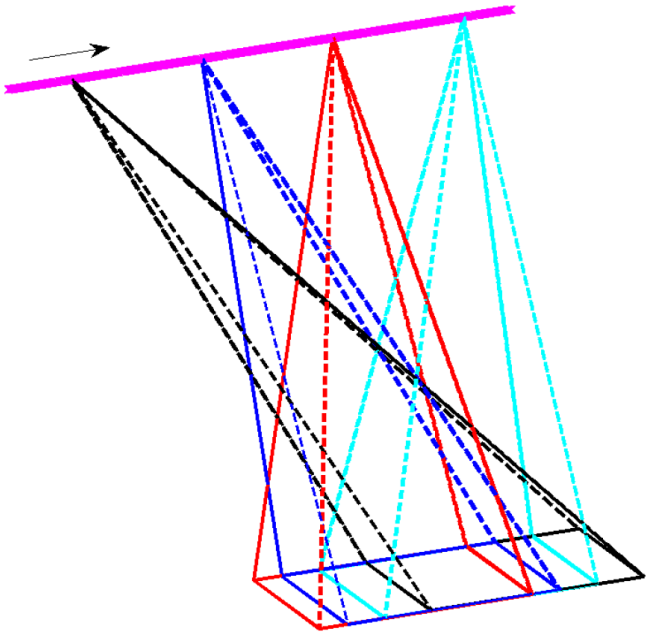
Can we do more? Sliding Mode Array (IGARSS 2013)



Conventional sliding mode:
Beam sliding in area of interest



Randomized sliding mode
Beam randomly steered
in area of interest.

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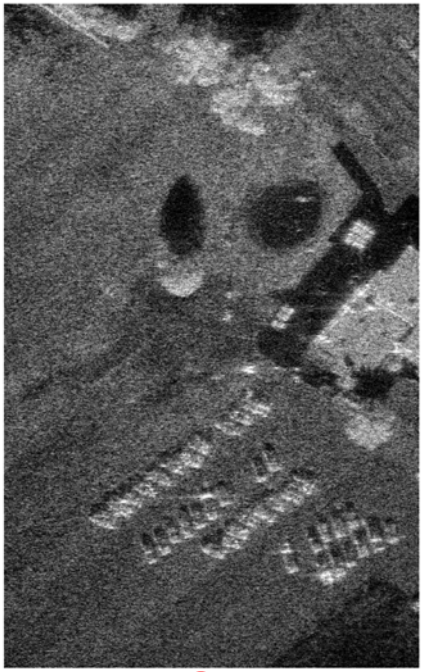
Simulation Results

MITSUBISHI ELECTRIC
Changes for the Better

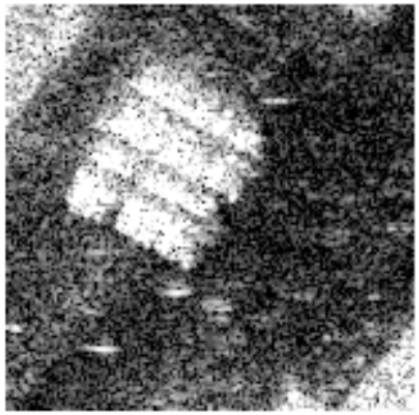
True Reflectivity

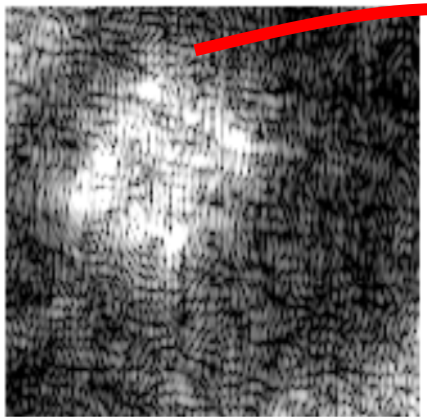
Conventional

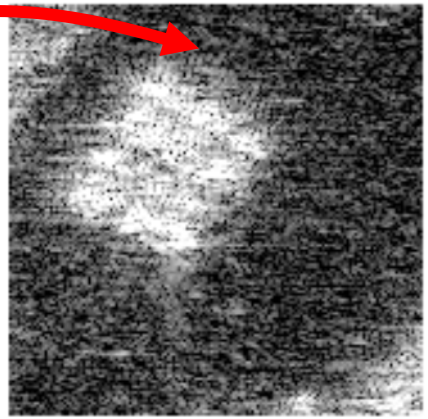
Randomized



10dB increase in SNR



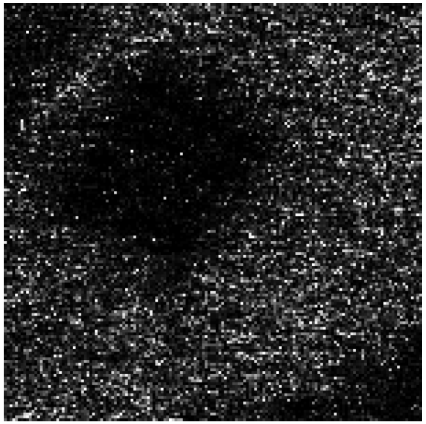




Phase Error

Conventional

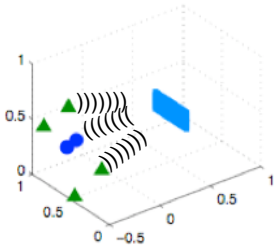
Randomized



26% reduction in Phase Error

Today

Computational Sensing Principles

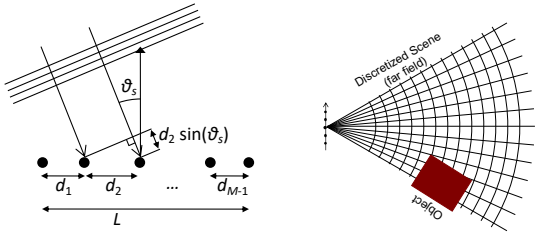


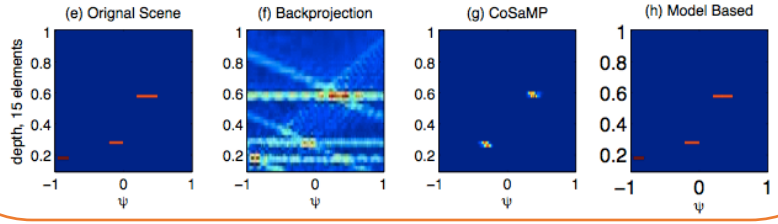
$$y_l(t) = x_n p_s(t - \tau_{s,l,n})$$
$$\Longleftrightarrow$$
$$Y_{l,f} = x_n P_{s,f} e^{-j\omega_f \tau_{s,l,n}}$$

$$\underbrace{\mathbf{y}}_{\text{Received data}} = \underbrace{\mathbf{A}}_{\substack{\text{Sensing Matrix} \\ \text{(determined by system design)}}} \underbrace{\mathbf{x}}_{\substack{\text{Scene} \\ \text{(unknown)}}}$$

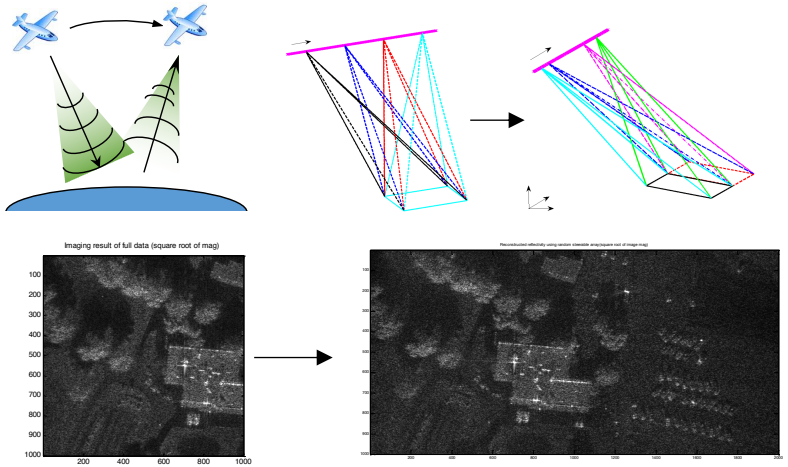
$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda R(\mathbf{x})$$

Radar and Array Processing

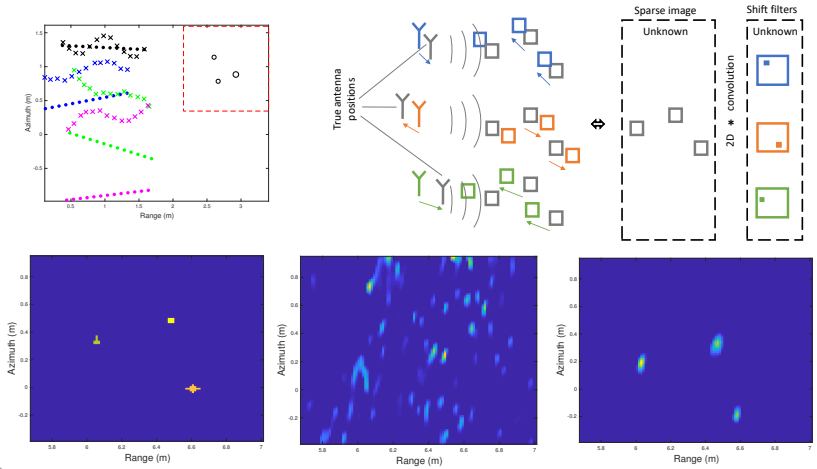




Synthetic Aperture Radar



Distributed Array Processing



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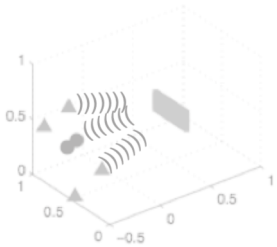
Today

Computational Sensing Principles



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$$\underset{\text{Received data}}{\mathbf{y}} = \underset{\substack{\text{Sensing Matrix}\\ \text{(determined by system design)}}}{\mathbf{A}}\ \underset{\substack{\text{Scene}\\ \text{(unknown)}}}{\mathbf{x}}$$

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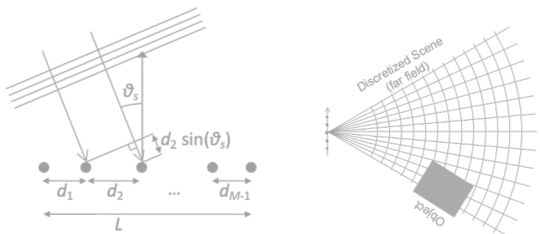
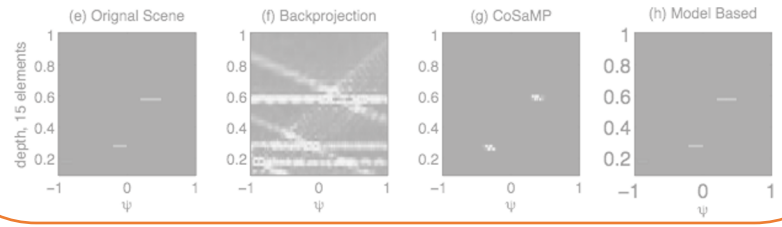
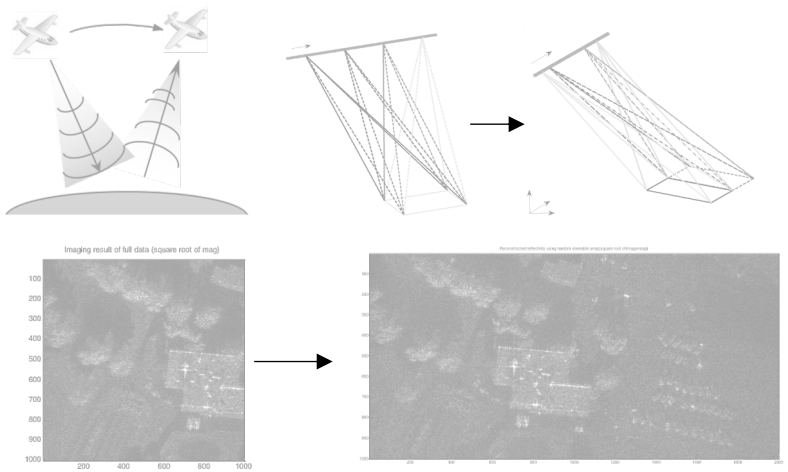
Radar and Array Processing

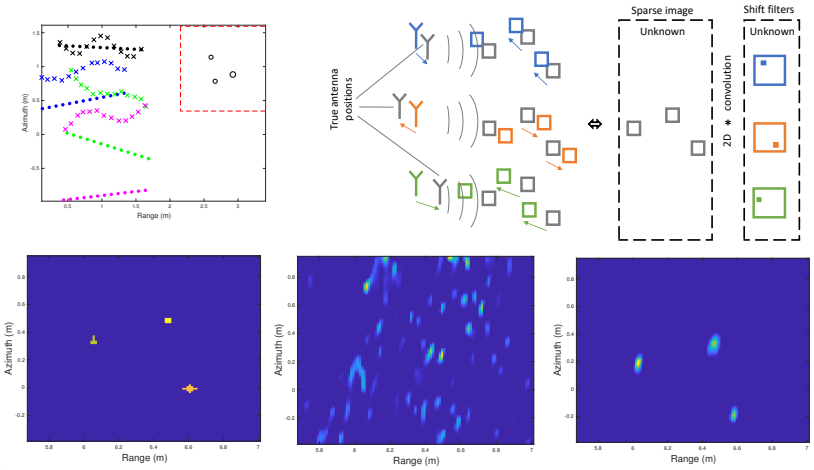




Synthetic Aperture Radar



Distributed Array Processing



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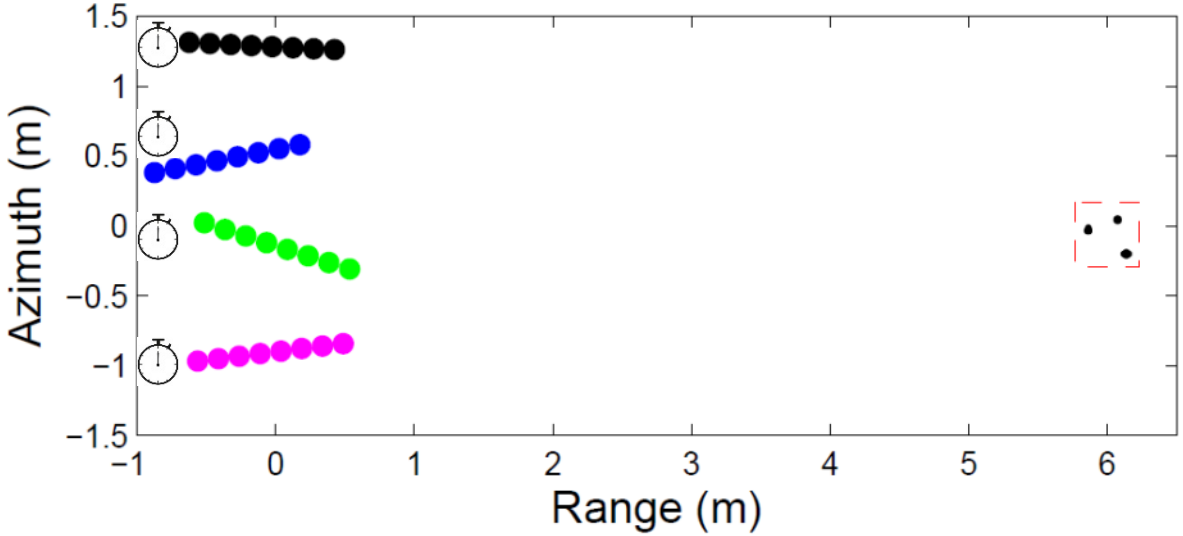
Distributed Radar

- Several spatially distributed radar platforms coordinating
  - Large aperture → High resolution
  - Small cheap platforms → Inexpensive, fault tolerant, robust, low maintenance…
- Main Challenges
  - Clocks are difficult to synchronize
  - Position of each platform not accurately known



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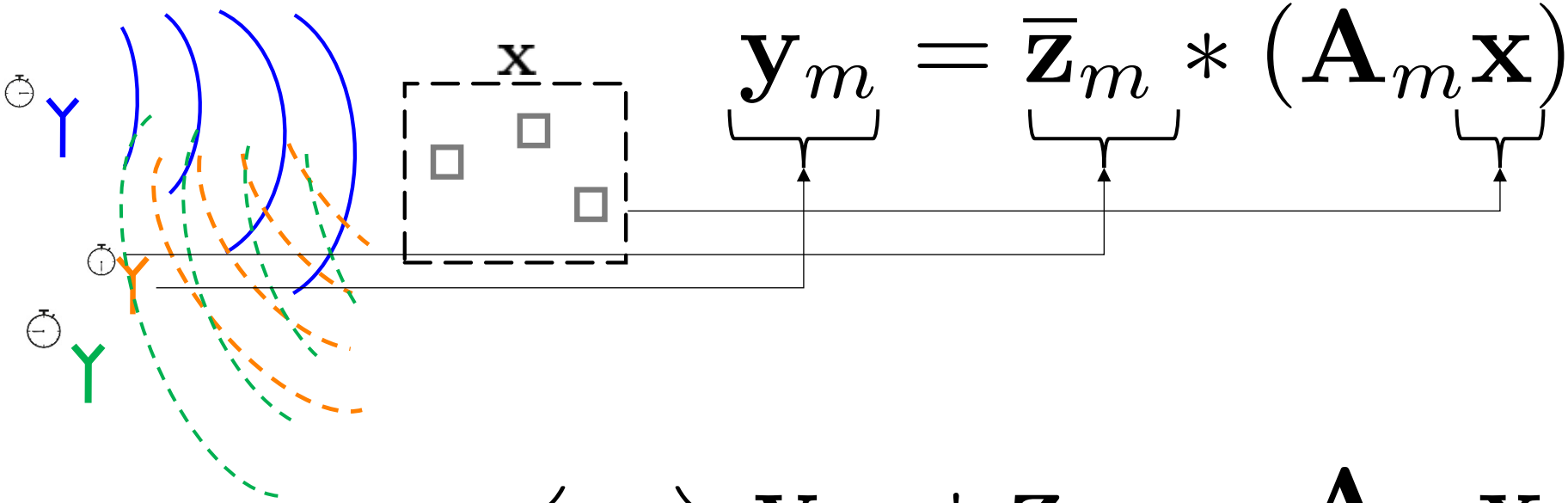
Problem 1: Imperfect Synchronization

- **Main intuition:** Timing shifts in the data can be modeled as a convolution in time with a 1-sparse kernel modeling the time delay



$$\Longleftrightarrow \mathbf{y}_m * \mathbf{z}_m = \mathbf{A}_m \mathbf{x}$$

$$\Longleftrightarrow \mathbf{A}_m \mathbf{x} - \mathbf{y}_m * \mathbf{z}_m = 0$$

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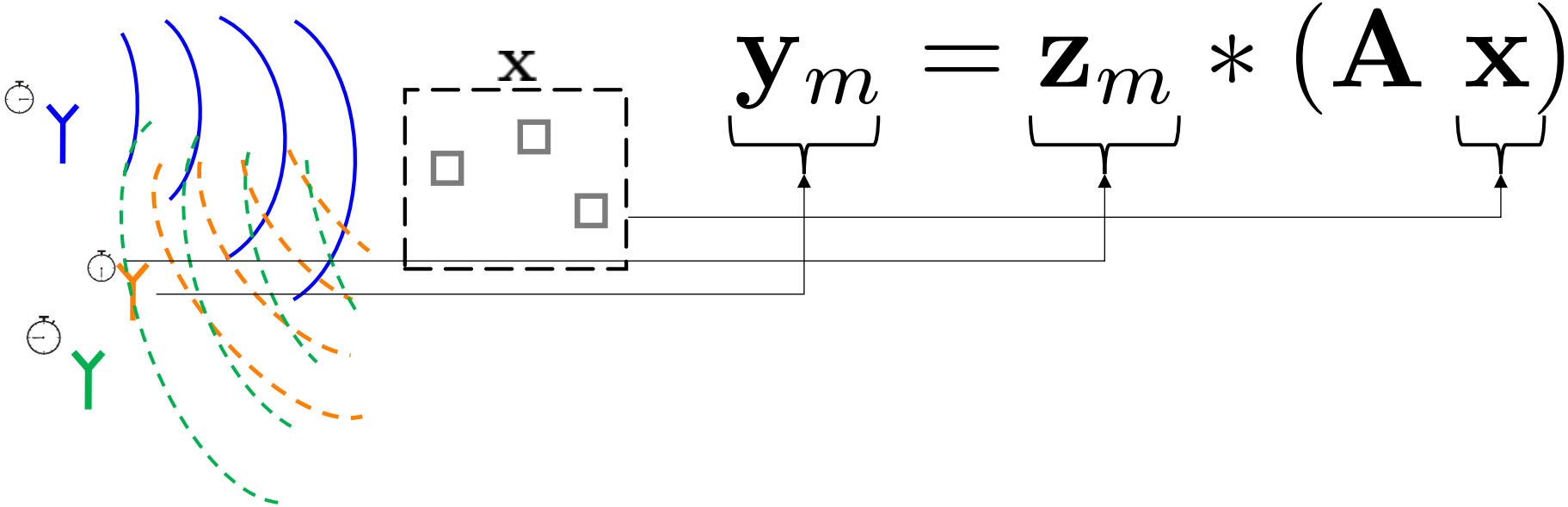
Problem 1: Imperfect Synchronization

- **Main intuition:** Timing shifts in the data can be modeled as a convolution in time with a 1-sparse kernel modeling the time delay



$$\Longleftrightarrow \begin{bmatrix} \widetilde{\mathbf{A}}_m & -\mathbf{F} \end{bmatrix} \begin{bmatrix} \overline{\mathbf{z}}_m \\ \mathbf{x} \end{bmatrix} = \mathbf{0}$$

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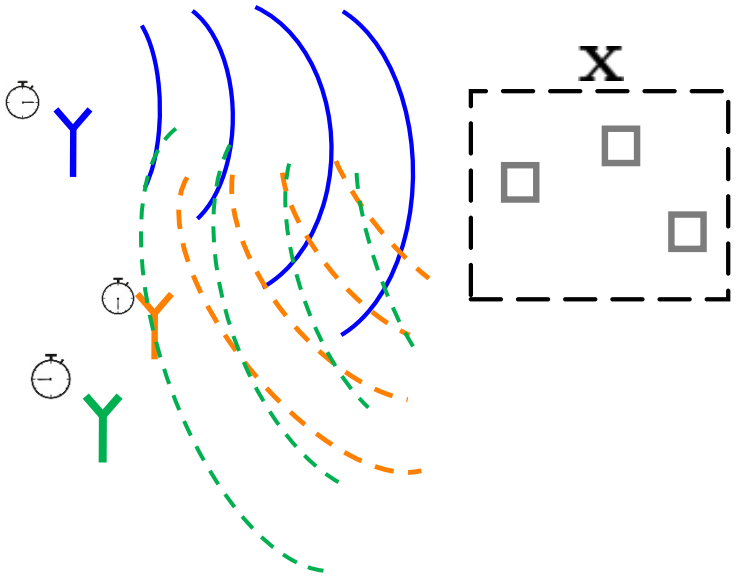
Computational Formulation



$$\begin{bmatrix} \widetilde{\mathbf{A}}_m & -\mathbf{F} \end{bmatrix} \begin{bmatrix} \overline{\mathbf{z}}_m \\ \mathbf{x} \end{bmatrix} = \mathbf{0}$$

- Scene is sparse, shifts are sparse
- All-zeros happens to be a (trivial) solution
- However, delays positive and sum up to 1
- Scene also (typically) positive, non-zero

$$\underset{\mathbf{x},\{\mathbf{z}_m\}_{m=1}^{M}}{\text{minimize}} \quad \lambda_x \|\mathbf{x}\|_1 + \lambda_z \sum_{m=1}^{M} \|\mathbf{z}_m\|_1 + \left\| \begin{bmatrix} \widetilde{\mathbf{A}}_1 & -\mathbf{F} & \Theta & \Theta & \cdots & \Theta \\ \widetilde{\mathbf{A}}_2 & \Theta & -\mathbf{F} & \Theta & \cdots & \Theta \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \widetilde{\mathbf{A}}_M & \Theta & \Theta & \Theta & \cdots & -\mathbf{F} \\ \gamma \mathbf{1}_N^T & \mathbf{0}_P^T & \mathbf{0}_P^T & \mathbf{0}_P^T & \cdots & \mathbf{0}_P^T \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{z}_1 \\ \mathbf{z}_2 \\ \vdots \\ \mathbf{z}_M \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ \gamma c \end{bmatrix} \right\|_2^2$$

$$\text{subject to:} \quad \mathbf{x} \geq \mathbf{0}_N \,,\; \mathbf{z}_m \geq \mathbf{0}_P \,,\; \mathbf{1}^T \mathbf{z}_m = 1 \,,\; \forall m \qquad (11)$$

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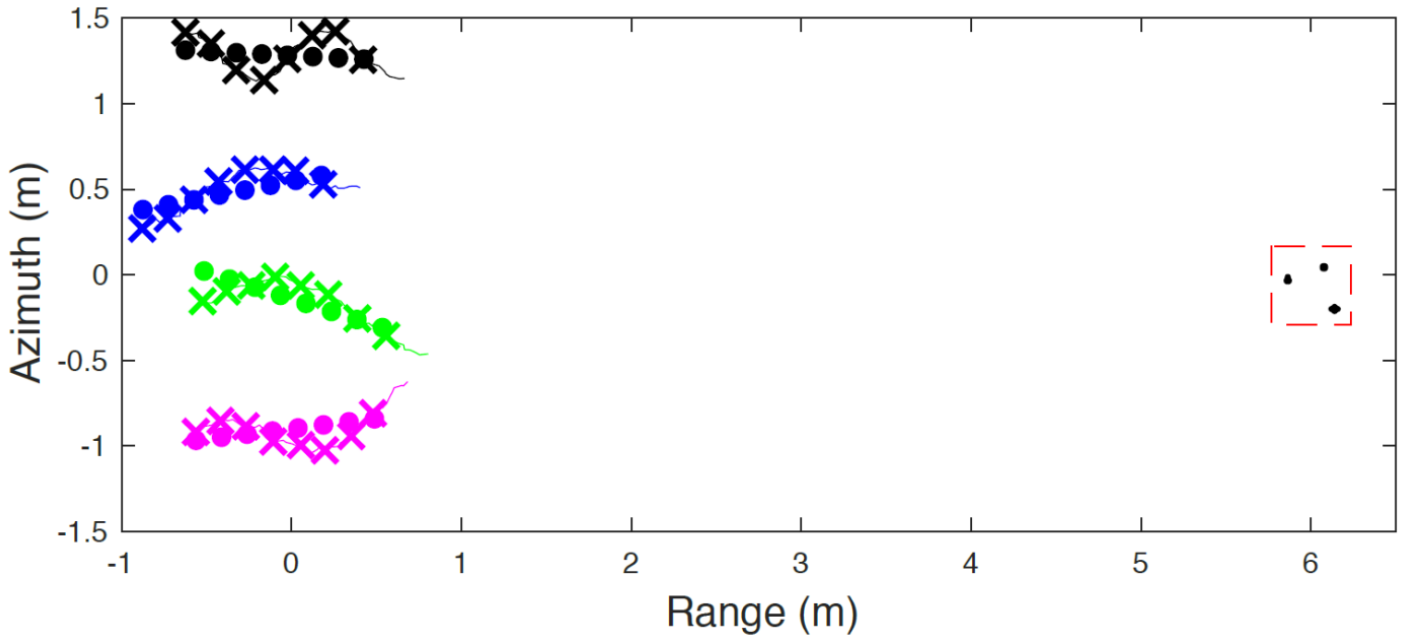
Experimental Results

- 32 antennas split into 4 arrays.
- 9 GHz BW Differential Gaussian pulse centered at 6 GHz.
- Timing error up to ±1ns



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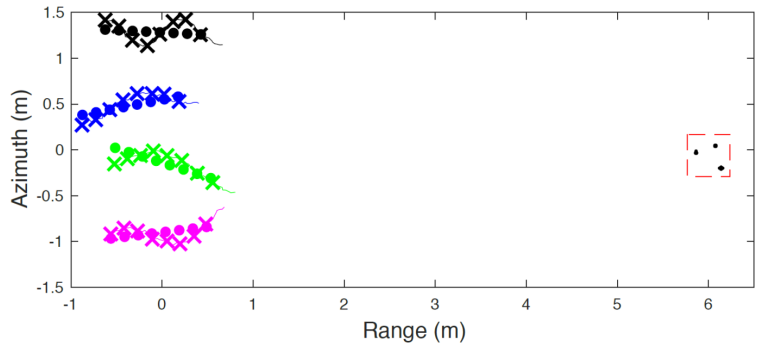
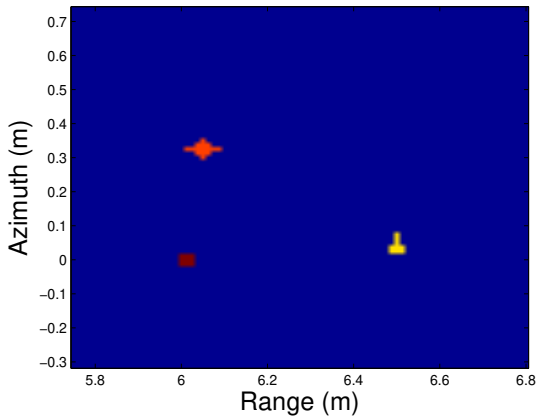
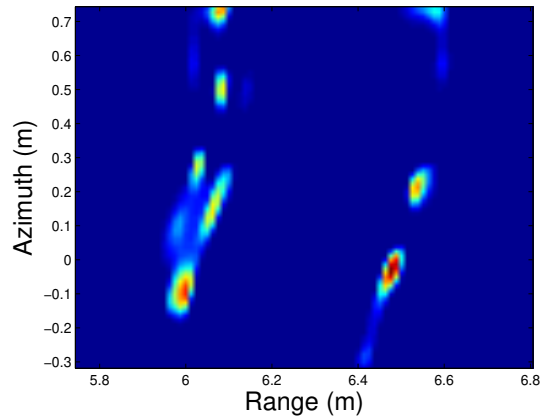


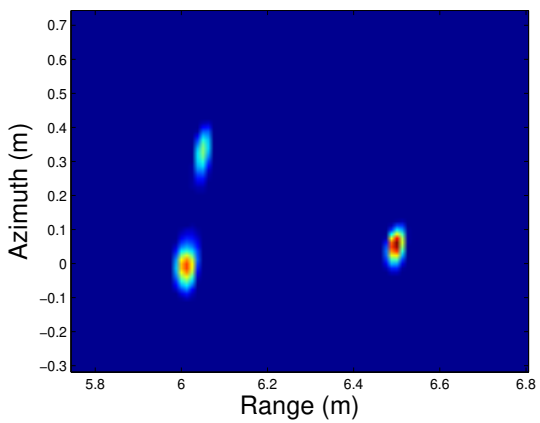
Original Scene



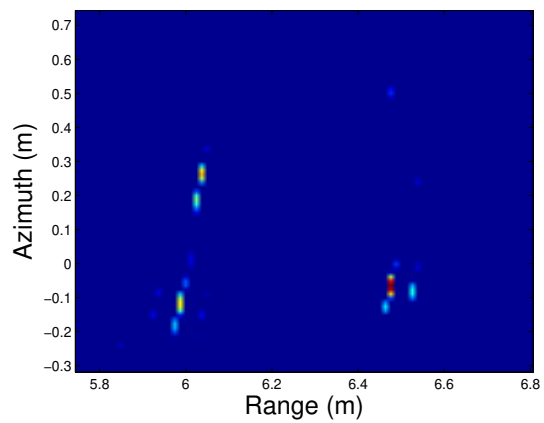
Timing Error Ignored



Synchronized System



Timing Error Corrected



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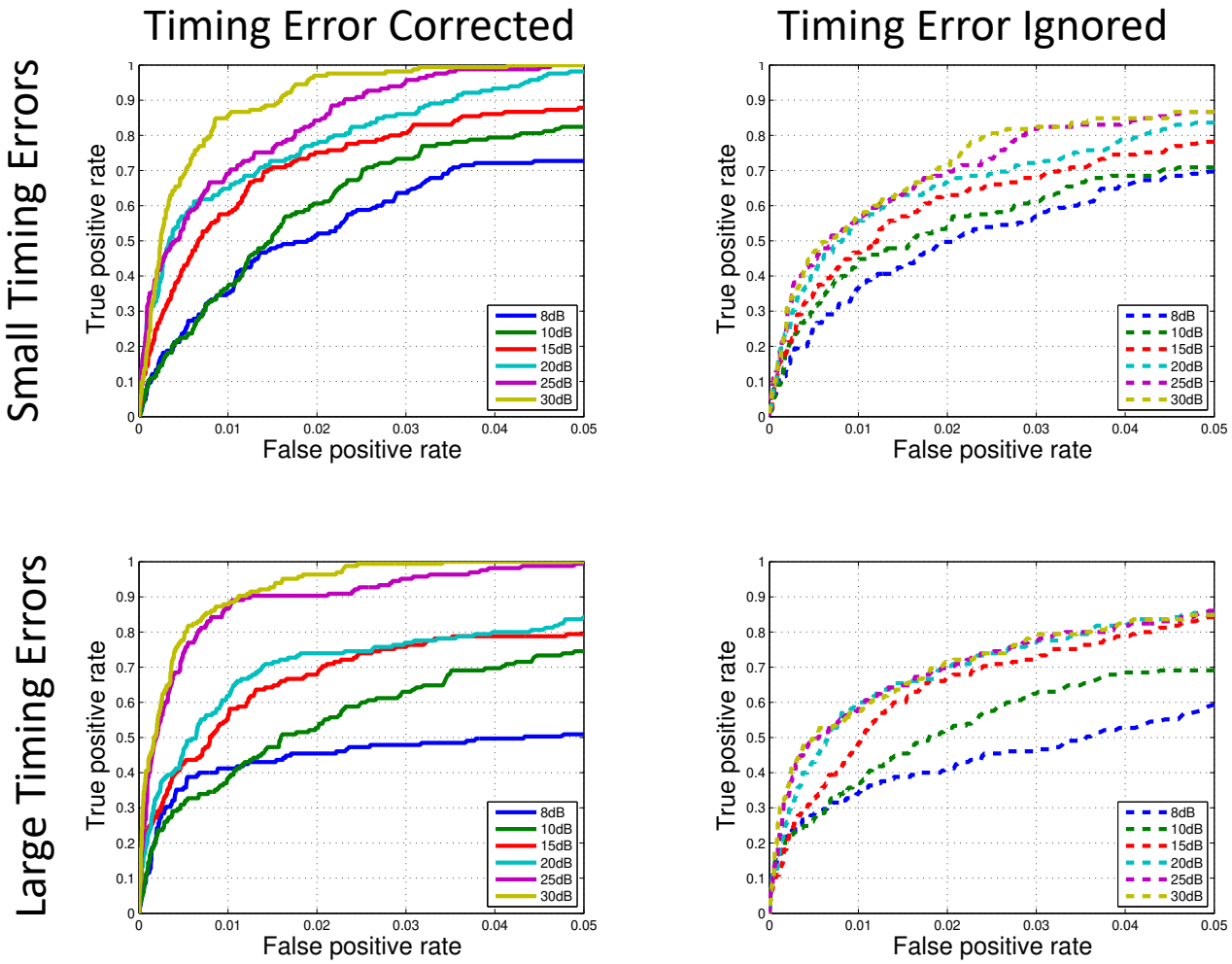
Experimental Results



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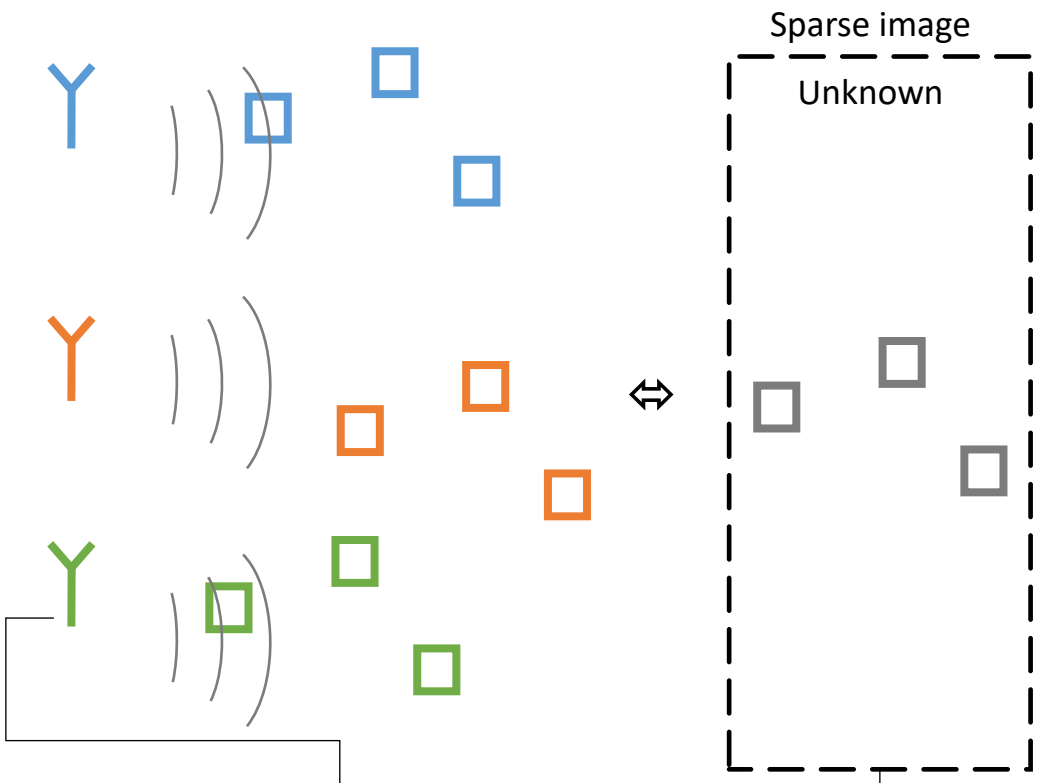
Problem 2: Unknown Positions

- **Main intuition:** Unknown position shift of a transmitter-receiver pair is equivalent to unknown shift of the image in space



$$\mathbf{y}_m = \mathbf{A} \ \mathbf{x}$$

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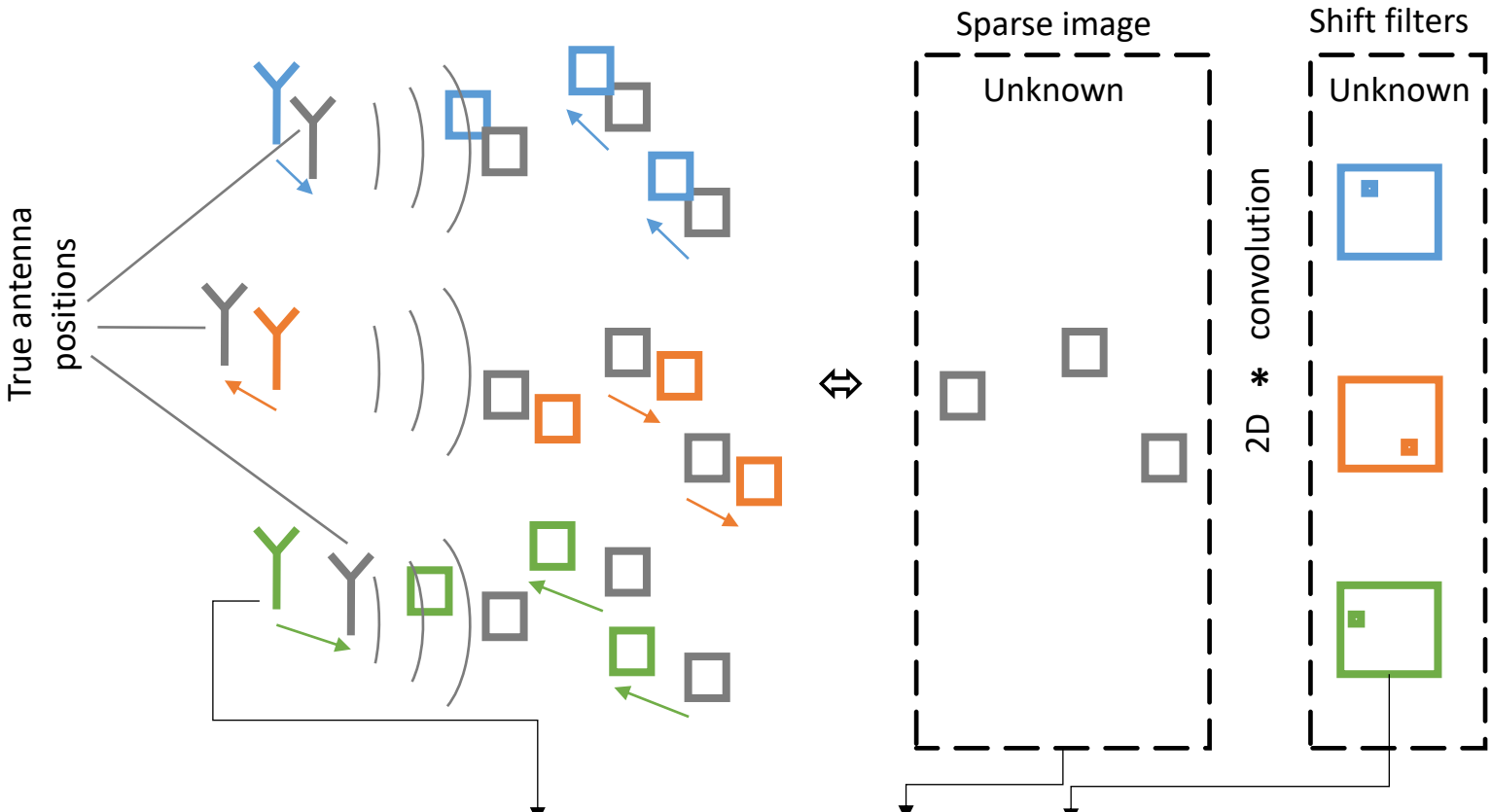

$$\mathbf{y}_m = \mathbf{A}\left(\mathbf{x} * \mathbf{h}_m\right)$$

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Computational Formulation

$$\mathbf{y}_m = \mathbf{A}\left(\boxed{\mathbf{x}} * \boxed{\mathbf{h}_m}\right)$$

Data — Sensing Operator — Scene — Shift Kernel

- Problem of two unknowns
  - Generally under-determined
  - But we know shift kernels are sparse (1-sparse, in fact)
  - The scene is also sparse

  $\Longrightarrow$ We can still formulate it as a minimization

$$\widehat{\mathbf{x}}, \widehat{\mathbf{h}}_m = \arg\min_{\mathbf{x},\mathbf{h}_m} \sum_m \left(\|\mathbf{y}_m - \mathbf{A}(\mathbf{x} * \mathbf{h}_m)\|_2^2 + \rho \|\mathbf{h}_m\|_1 \right) + \lambda \|\mathbf{x}\|_1$$

$$\text{s.t. } \mathbf{1}^T \mathbf{h}_m = 1$$

- Not a convex problem, harder to solve
  - We alternate between solving for $\mathbf{x}$ and $\mathbf{h}_m$

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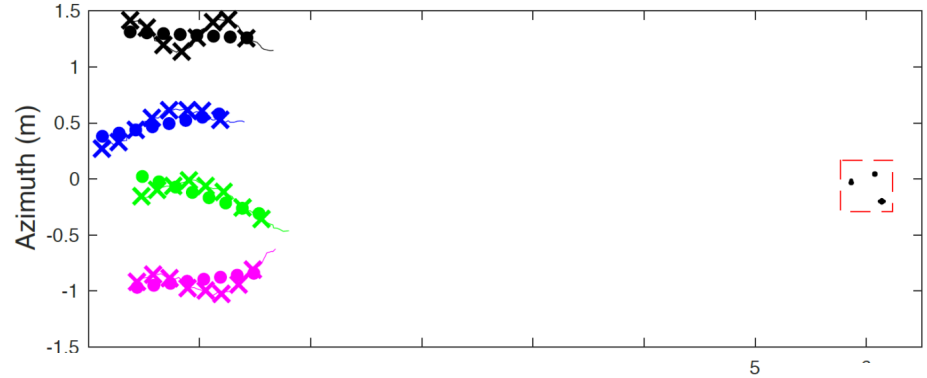
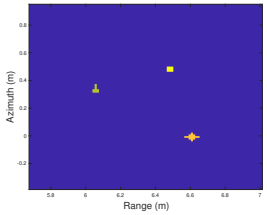
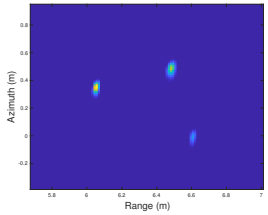
Simulation Results

- 32 antennas split into 4 arrays.
- 9 GHz BW Differential Gaussian pulse centered at 6 GHz.
- Average position error ~2λ; maximum error at 3.5λ

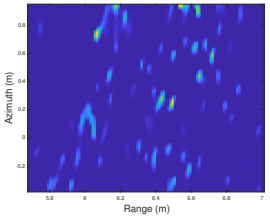




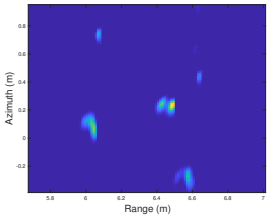
Actual Scene



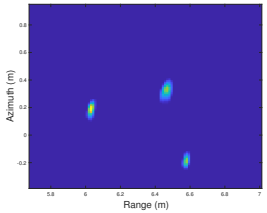
Positions Known



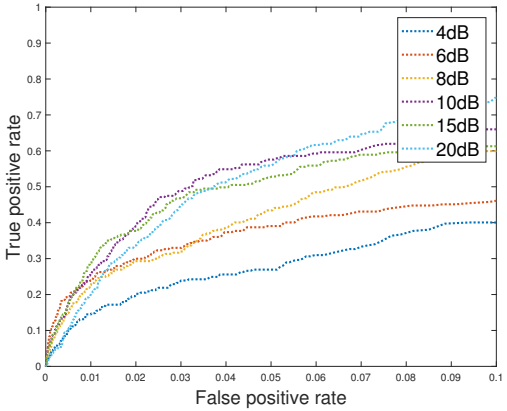
Position Error Ignored

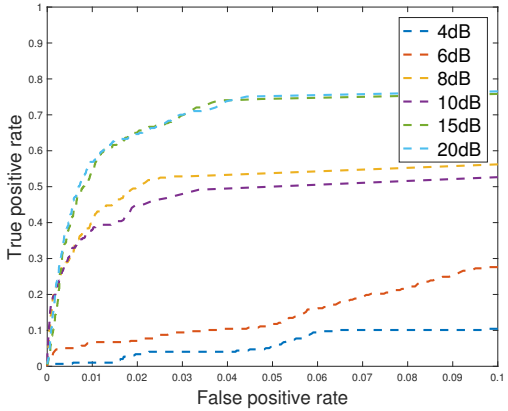


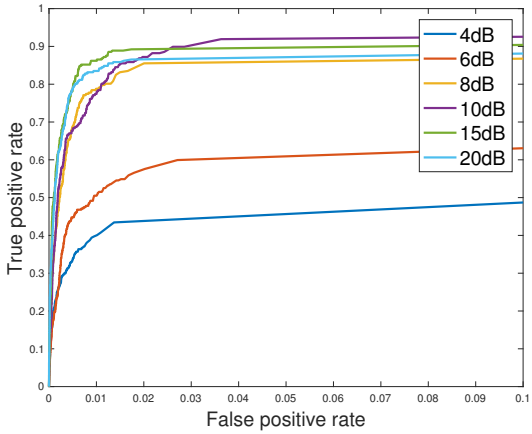
Measurement phase Correction (classical)



Position Error Corrected (this talk)







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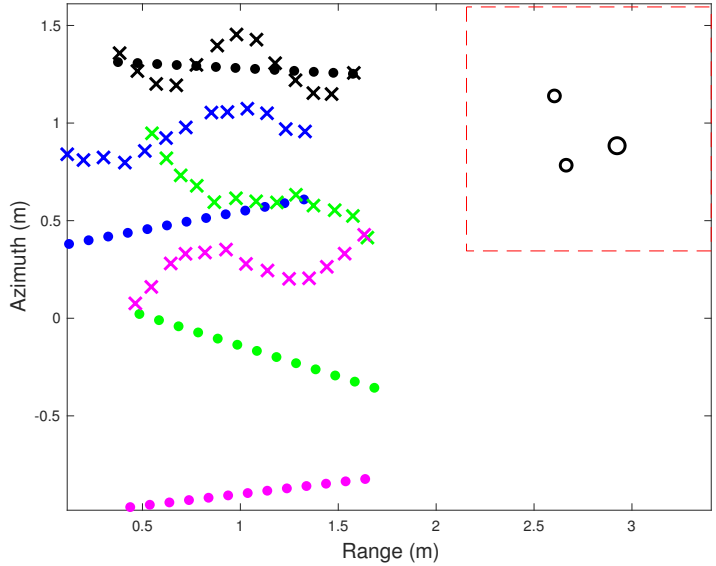
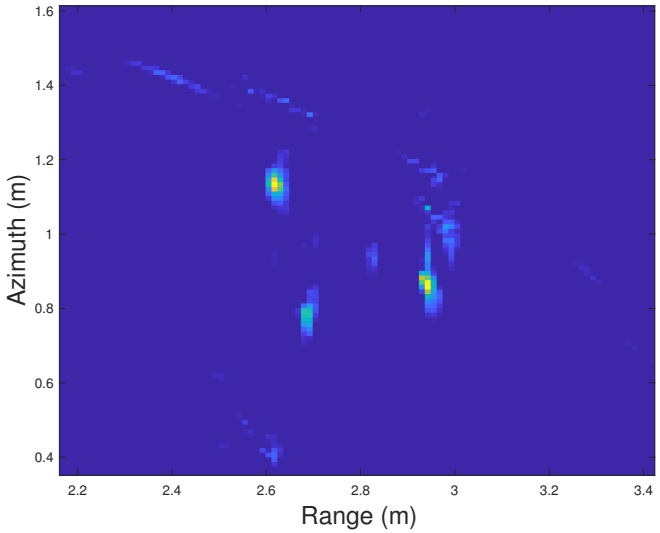
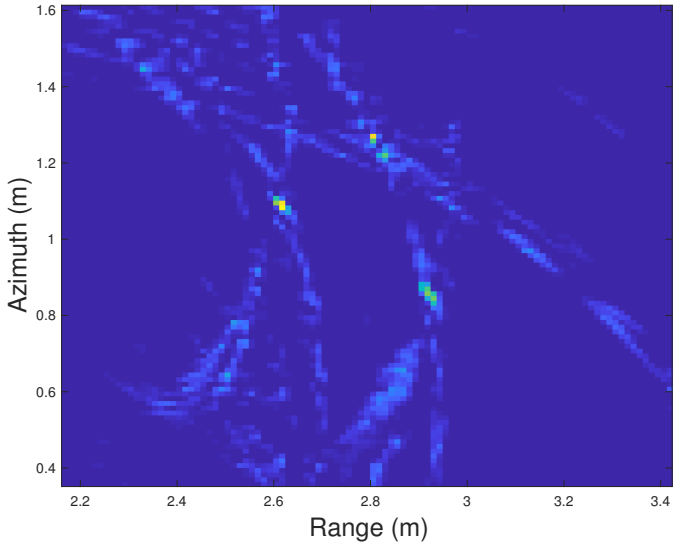
Experimental Results

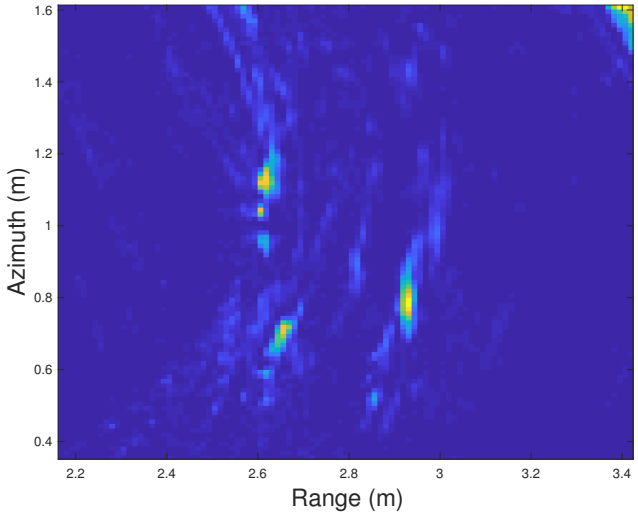




True Positions



Position Error Ignored



Position Error Corrected

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Take-home Message

- **Computation** should have a symbiotic relationship with **sensing**
  - Important to balance the **trade-off** between hardware complexity and computation
  - Be aware of complexity cost and use computation where it matters

- Good **modeling** of the system and the signal **is key**
  - Linearity goes a long way!
  - Signal models are your friends

- **Inverse problem framework** is very powerful and very generic
  - Makes model enforcement easy

Questions/Comments?

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