The Relationship Between Detection Algorithms for Hyperspectral and Radar Applications

Nirmal Keshava, Stephen M. Kogon, Dimitris Manolakis

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MIT Lincoln Laboratory
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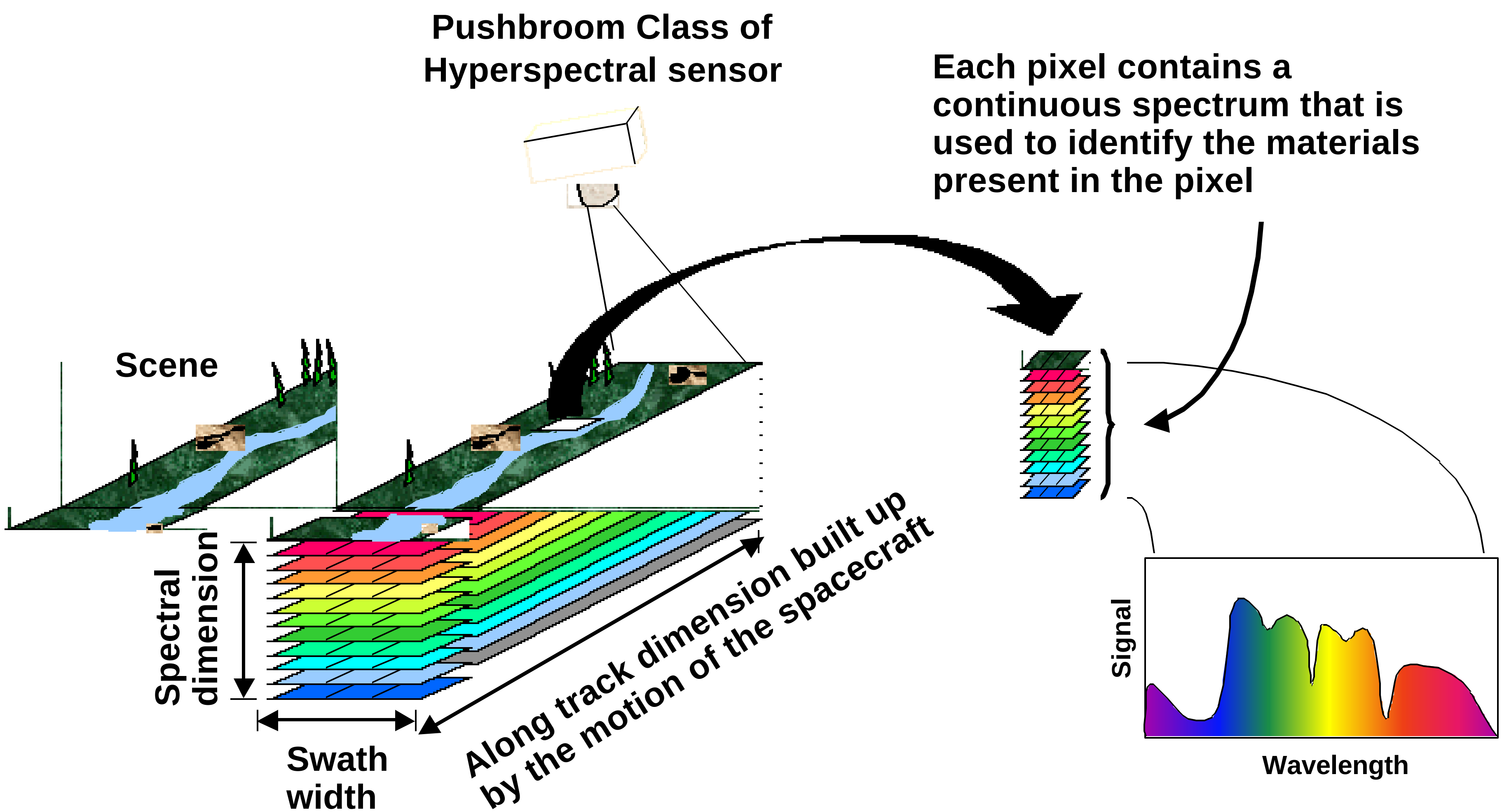
Objective

- **Overview of hyperspectral sensing**
- **Demonstrate how and why detection algorithms for hyperspectral imagery are related to detection algorithms for MTI radar**
  - **Similar physical assumptions**
  - **Common signal model**
- **Illustrate detection in hyperspectral imagery with real data and familiar detectors**

Outline

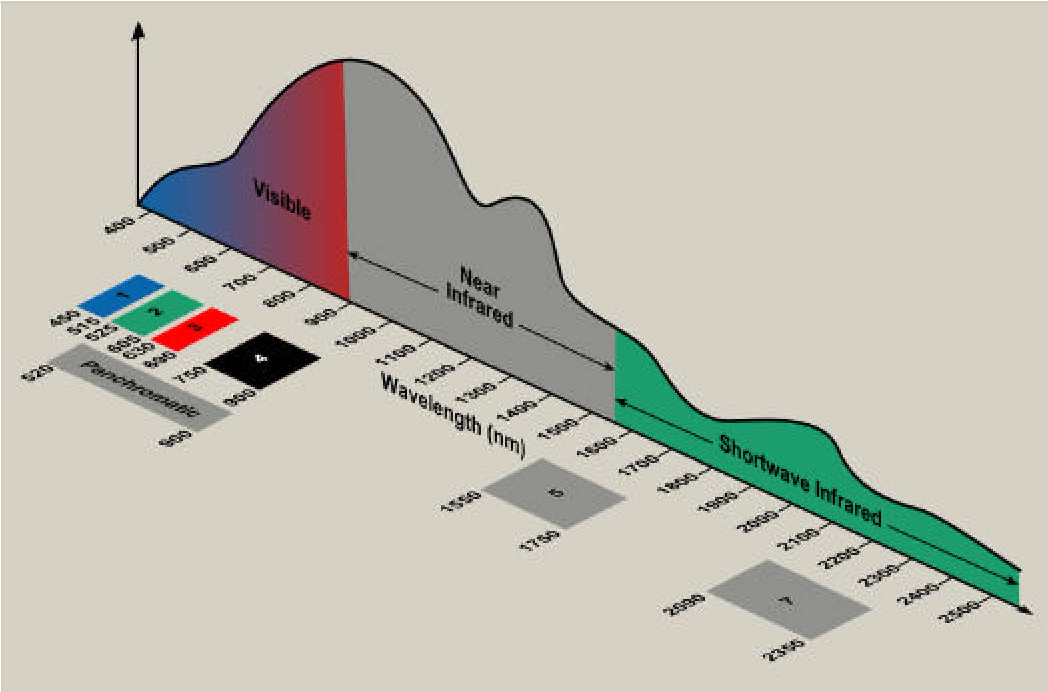
- Introduction to hyperspectral sensing
- Signal models
- Detection models
- Hyperspectral detection results
- Conclusion

Hyperspectral Imaging (HSI) Concept



Hyperspectral Sensing

- **Hyperspectral imaging (HSI) is a form of *passive* imaging**
  - **Extension of multispectral sensing (e.g., Landsat)**
  - **Hundreds of contiguous, real-valued spectral bands**
  - **Spatial resolution is a function of Instantaneous Field of View (IFOV) and altitude**



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- Signal models
  - Hyperspectral sensing
  - MTI radar
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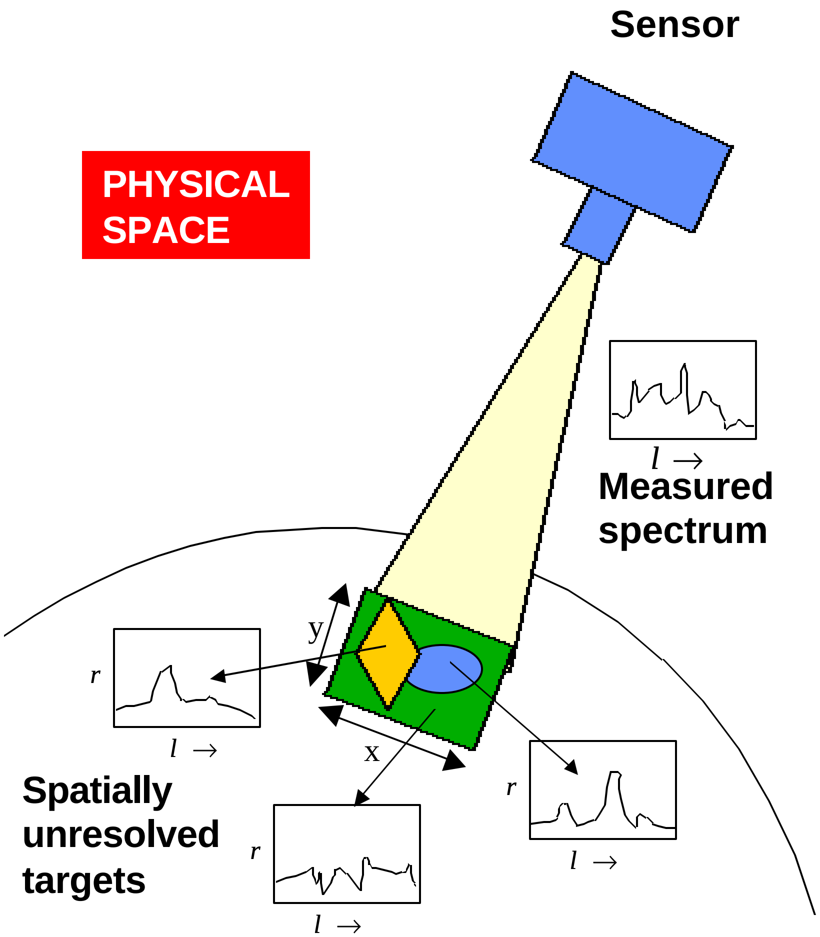
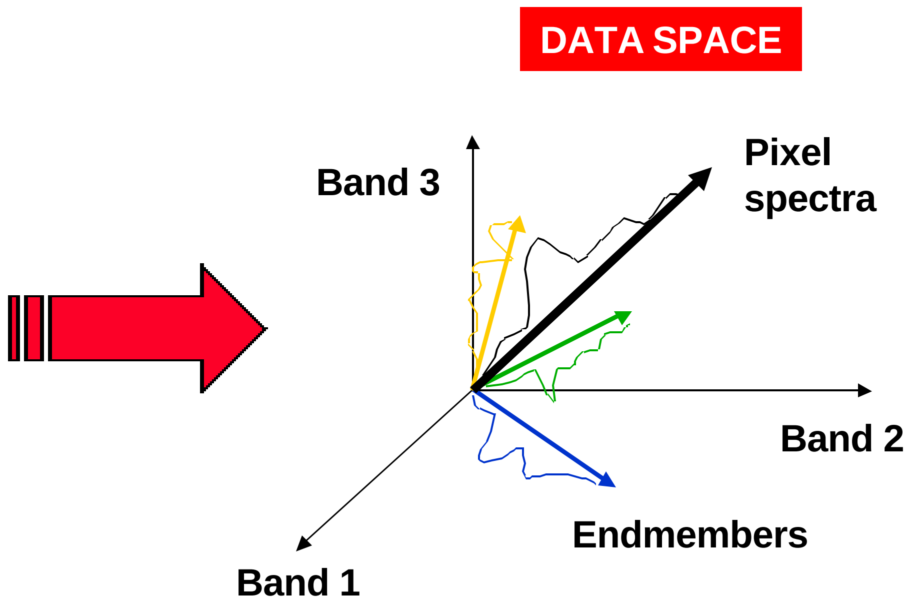
Modeling of Spatially Unresolved (Mixed) Pixels





SIGNAL PROCESSING

- Unmixing
  - Find endmembers
  - Compute abundances
- Classification
- Detection

Linear Mixing Model (LMM)

Target and Background Modeling

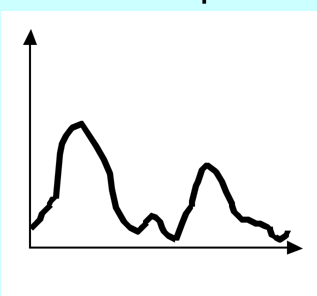
abundance

Test pixel $$\boldsymbol{x} = \sum_{k=1}^{P_T} a_k \boldsymbol{s}_k + \sum_{k=P_T+1}^{P_T+P_B} a_k \boldsymbol{s}_k + n$$

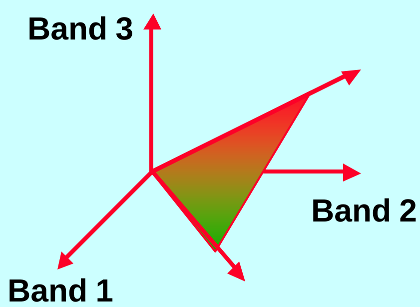
end member

LINEAR MIXING MODEL

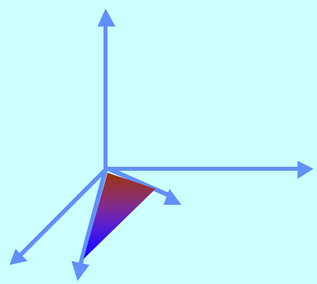
Measured spectrum



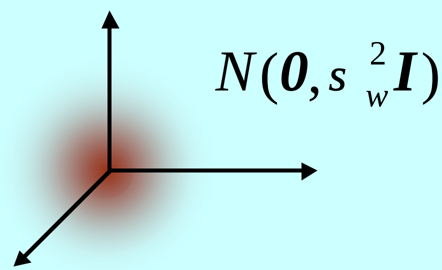
Target subspace



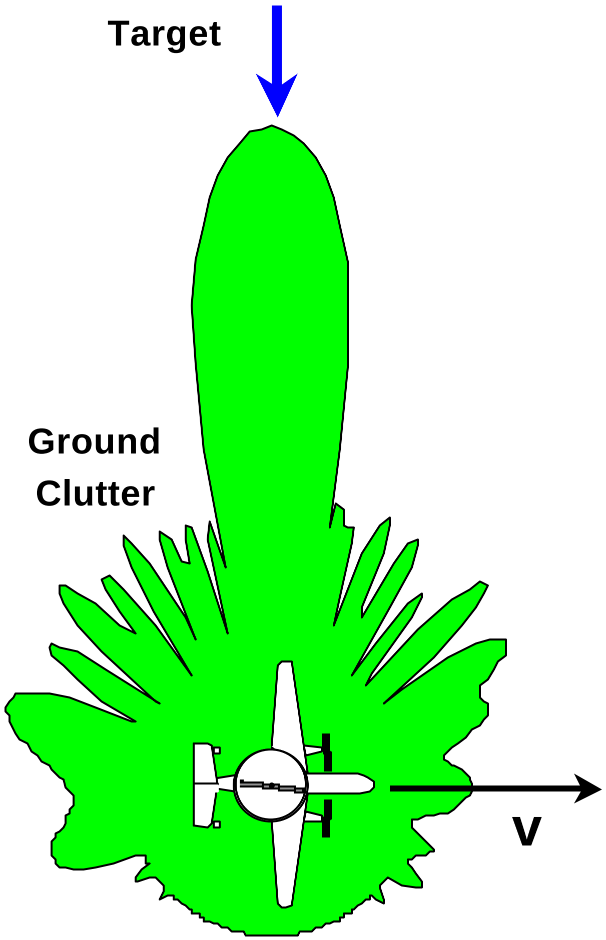
Background subspace



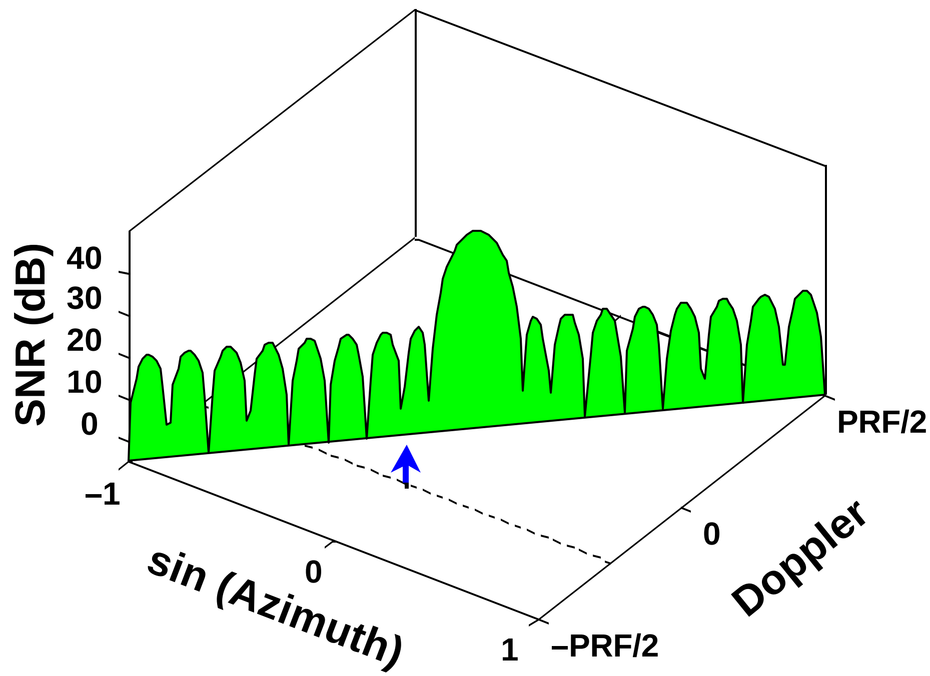
Noise hyper-sphere



MTI Radar



Surveillance Radar

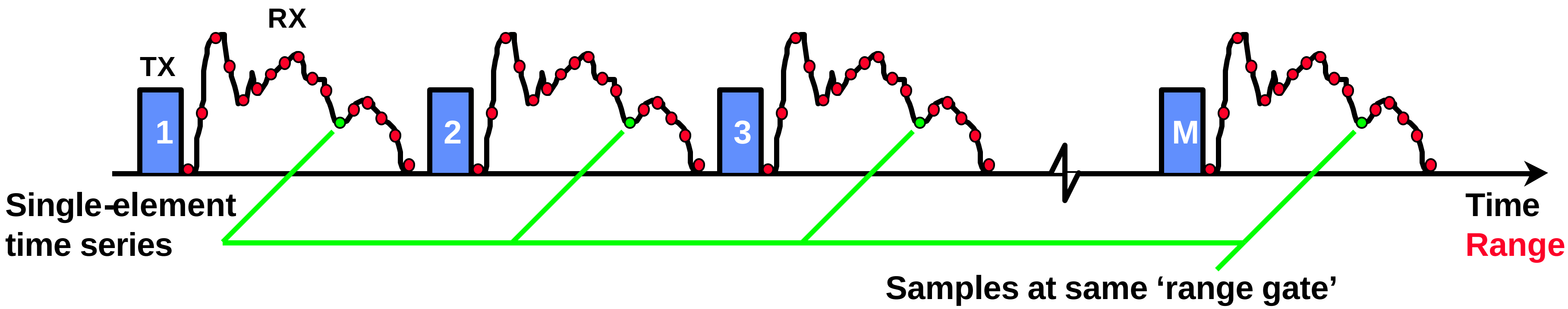


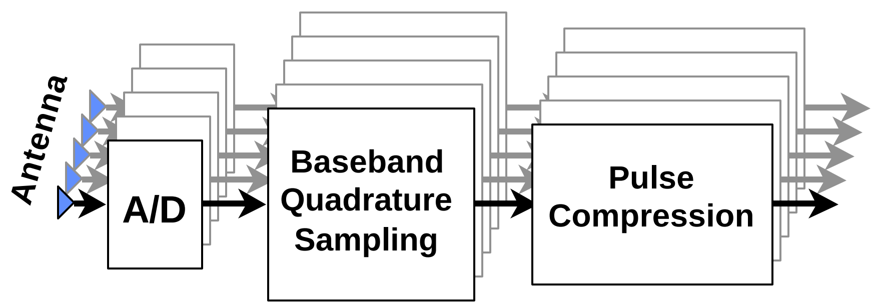
Two-dimensional filtering required to cancel interference

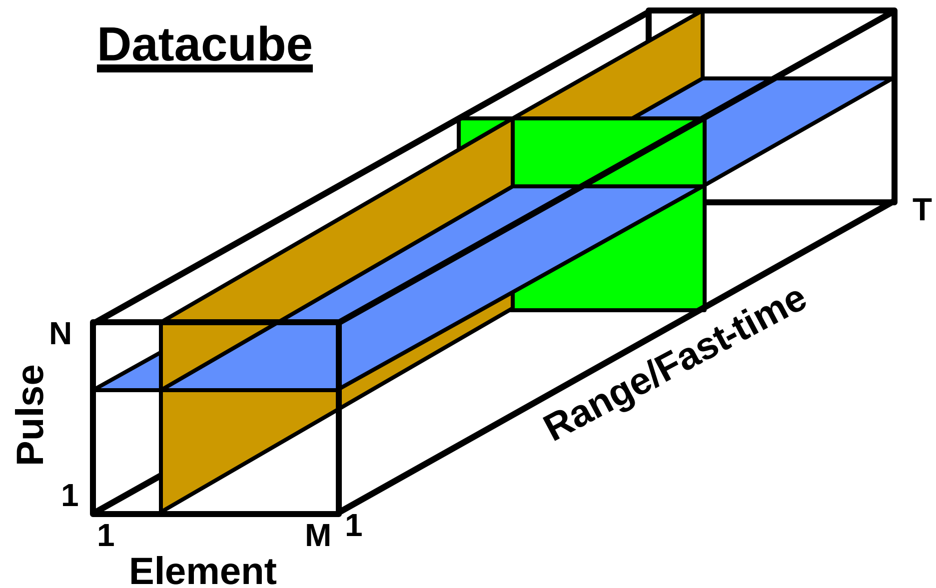
Space-Time Adaptive Processing

(STAP)

Pulsed Radar Datacube







Measurement		Physical Quantity
Pulse	⇨	Doppler (velocity)
Element	⇨	Angle
Fast-time	⇨	Range

STAP Radar Signal Model

- **Space-time snapshot for single target**

$$\mathbf{x} = \mathbf{t} + \mathbf{c} + \mathbf{n} \qquad\qquad \mathbf{t} = a\,\mathbf{v}(f, f)$$

- $\mathbf{v}(f, f)$ **is called the space-time <u>steering vector</u>**

- **Space-time interference (clutter, noise) covariance is**

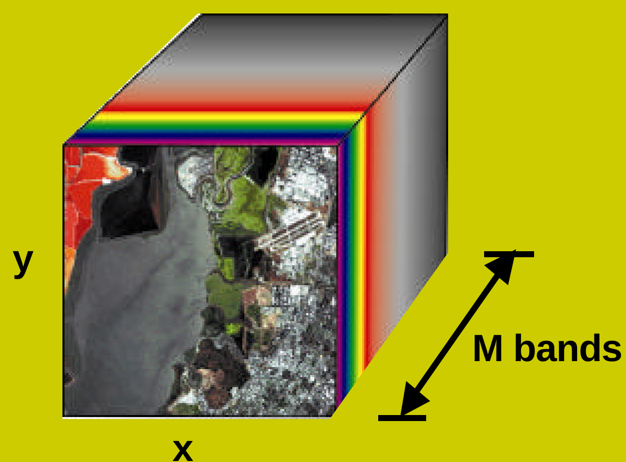
$$\mathbf{R} = E\left\{(\mathbf{c}+\mathbf{n})\,(\mathbf{c}+\mathbf{n})^H\right\} = \mathbf{R}_c + \mathbf{R}_n$$

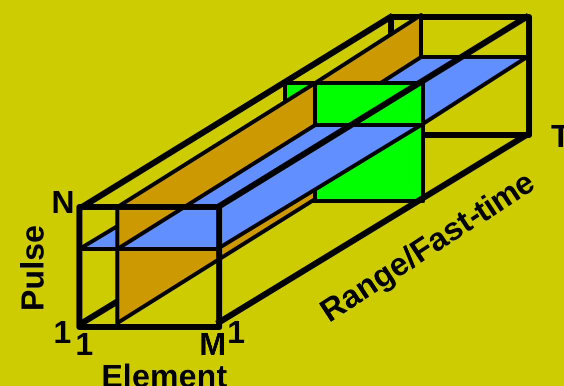
Hyperspectral Imaging and MTI Radar

Summary of Properties

	Hyperspectral Imaging	MTI Radar
System	• Passive, incoherent sensing • Resolution is a function of detector IFOV and altitude	• Active, coherent sensing • Resolution is a function of signal bandwidth and aperture length
Signal Model	• LMM assumes distinct spectra mix linearly • Real spectra are sum of <u>endmembers</u> weighted by <u>abundances</u> $\mathbf{x} = a\mathbf{s} + \mathbf{b} + \mathbf{n}$	• Components add linearly to yield received signal • Complex array measurements are sum of <u>steering vectors</u> weighted by <u>RCS</u> values $\mathbf{x} = a\,\mathbf{v} + \mathbf{c} + \mathbf{n}$

Data Cube





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  - Hyperspectral sensing
  - MTI radar
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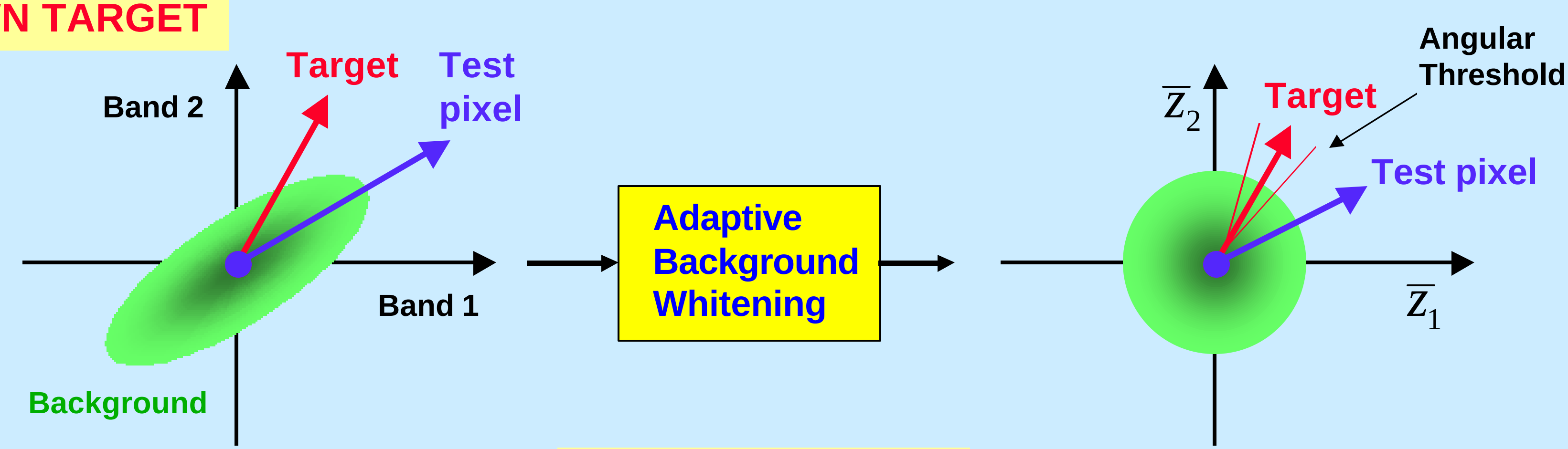
Adaptive HSI Detection

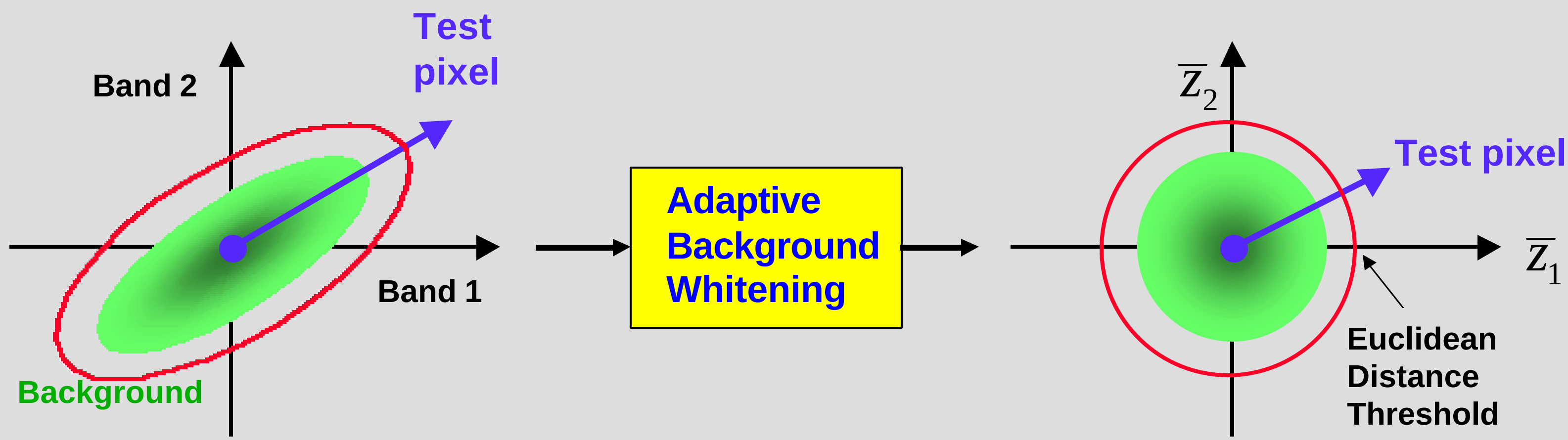
Known and Unknown Targets

KNOWN TARGET

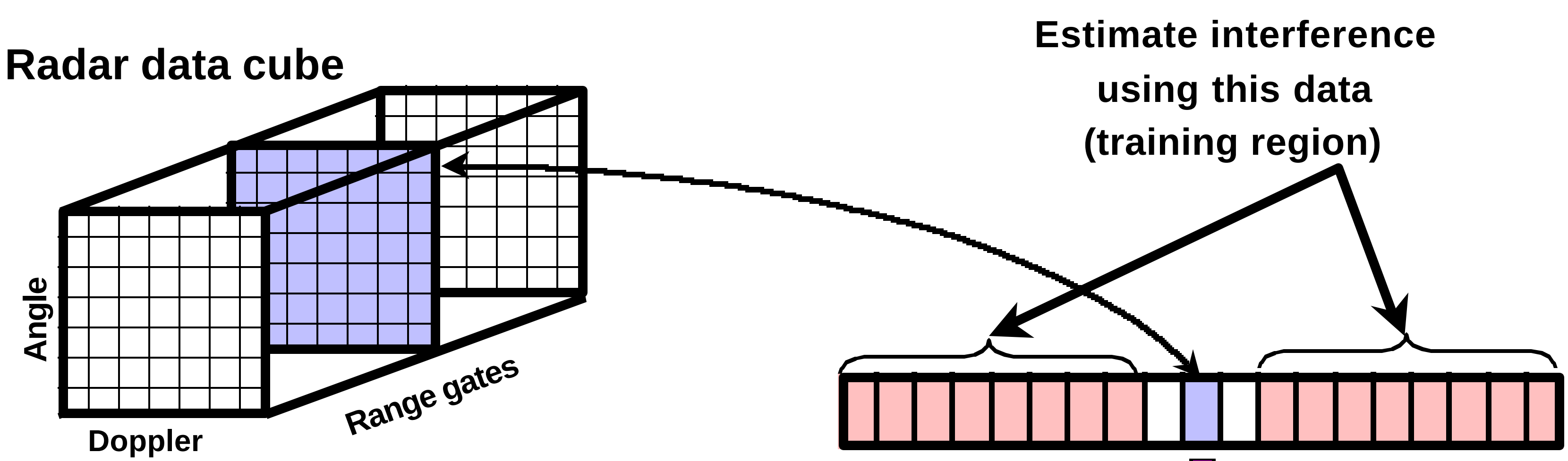


$$\hat{\boldsymbol{R}} = \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{x}(n)\boldsymbol{x}^T(n)$$

UNKNOWN TARGET



Adaptive Detection in STAP Radar



$$\hat{\mathbf{R}} = \frac{1}{K}\sum_{k=1}^{K} \mathbf{x}(k)\,\mathbf{x}(k)^H$$

Estimate STAP Weights

$$\mathbf{w} = \hat{\mathbf{R}}^{-1}\mathbf{v}(f\,,\,f\,)$$

x → **STAP** → y → **Detector** ($y > g \rightarrow \mathrm{H0}$; $y < g \rightarrow \mathrm{H1}$) →

Hypothesis Testing:

$H0:\quad \mathbf{x} = \mathbf{t} + \mathbf{c} + \mathbf{n}$ — Target present

$H1:\quad \mathbf{x} = \mathbf{c} + \mathbf{n}$ — No target

Replacement and Additive Target Models

- **Hyperspectral detection has replacement targets**

$$H0: \quad \mathbf{x} = \mathbf{b} + \mathbf{n}$$

$$H1: \quad \mathbf{x} = f\,\mathbf{t} + (1 - f)\,\mathbf{b} + \mathbf{n}$$

- **Interference statistics**
  - Varies with $f, 0 \le f \le 1$
  - Target displaces background
- **Detection results**
  - Insufficient target data for ROC curves
  - No theoretical models

- **MTI radar detection has additive targets**

$$H0: \quad \mathbf{x} = \mathbf{c} + \mathbf{n}$$

$$H1: \quad \mathbf{x} = \mathbf{t} + \mathbf{c} + \mathbf{n}$$

- **Interference statistics**
  - Independent of target
  - Measure locally
- **Detection results**
  - ROC curves indicate P_D/P_{FA} values
  - Theoretical models for target

Comparison of HSI and MTI Detection

	Hyperspectral Imaging	MTI Radar
Task	• Known target – Detect target spectrum amid background • Unknown target – Detect pixels anomalous from background	• Moving target – Detect Doppler effect at specific range and angle – Use data after pulse compression
Covariance	• Interference covariance estimated from sample pixels – Dimension equals number of bands (~ 100--200) – Can use subset of bands	• Interference covariance estimated from local subset of pulse/element/range measurements – Better estimate – Avoids non-stationarity
Strategy	• Replacement target model • Known target – Measure spectral angle • Unknown target – Measure magnitude	• Additive target model • Moving target – Exploit coherency through beamforming and Doppler filtering – RCS and velocity are key parameters for target visibility

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- Hyperspectral detection results
  - Detection taxonomy
  - Sub-pixel target detection
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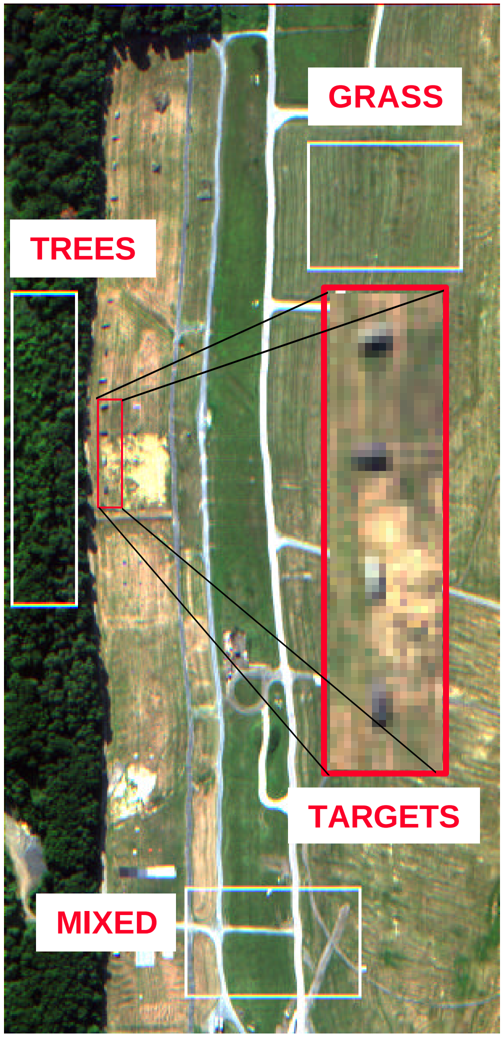
Taxonomy of Hyperspectral Detectors

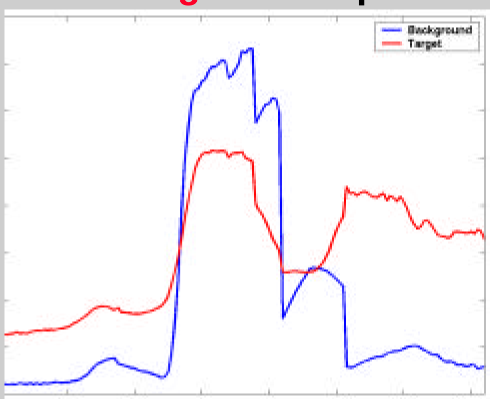
Noise model	Signal model	Available data	Test statistic $T(x)$	References	Comments
$\mathbf{R}$ = completely unknown interference (unstructured)	$\mathbf{s} = a\mathbf{s}_t$ known direction	$\boldsymbol{x}$ = test measurement $\{x_n\}_1^N$ = "signal-free" training data $\bar{\mathbf{R}} = \sum_{n=1}^{N} \mathbf{x}_n \mathbf{x}_n^T$ $\hat{\mathbf{R}} = \frac{1}{N}\bar{\mathbf{R}}$	$\dfrac{\lvert \mathbf{s}_t^T \bar{\mathbf{R}}^{-1}\mathbf{x}\rvert^2}{(\mathbf{s}_t^T \bar{\mathbf{R}}^{-1}\mathbf{s}_t)(1+\mathbf{x}^T\bar{\mathbf{R}}^{-1}\mathbf{x})}$	Generalized Likelihood Ratio Test (GLRT) Kelly (1986)	
			$\dfrac{\lvert \mathbf{s}_t^T \bar{\mathbf{R}}^{-1}\mathbf{x}\rvert^2}{\mathbf{s}_t^T \bar{\mathbf{R}}^{-1}\mathbf{s}_t}$	Adaptive Matched Filter (AMF) Robey et al (1992) Chen and Reed (1991)	$T_{CEM}(\mathbf{x}) = \dfrac{\mathbf{s}_t^T \bar{\mathbf{R}}^{-1}\mathbf{x}}{\mathbf{s}_t^T \bar{\mathbf{R}}^{-1}\mathbf{s}_t}$
			$\dfrac{\lvert \mathbf{s}_t^T \bar{\mathbf{R}}^{-1}\mathbf{x}\rvert^2}{(\mathbf{s}_t^T \bar{\mathbf{R}}^{-1}\mathbf{s}_t)(\mathbf{x}^T\bar{\mathbf{R}}^{-1}\mathbf{x})}$	Adaptive Coherence Estimator (ACE) Conte et al (1995) Scharf and McWhorter (1996)	$\mathbf{x} = \bar{\mathbf{R}}^{-1/2}\mathbf{x},\ \mathbf{s}_t = \bar{\mathbf{R}}^{-1/2}\mathbf{s}_t$ $\cos\theta = \dfrac{\lvert s_t^T x\rvert}{\lVert s_t\rVert \lVert x\rVert}$ $\mathbf{R} = \sigma^2\mathbf{I} \Rightarrow$ SAM
	$\boldsymbol{s} = \sum_{k=1}^{P} a_k \boldsymbol{s}_k = \boldsymbol{Sa}$ $1 \le P \le M$		$\dfrac{\mathbf{x}^T\bar{\mathbf{R}}^{-1}\mathbf{S}(\mathbf{S}^T\bar{\mathbf{R}}_v^{-1}\mathbf{S})^{-1}\mathbf{S}^T\bar{\mathbf{R}}^{-1}\mathbf{x}}{1+\mathbf{x}^T\bar{\mathbf{R}}^{-1}\mathbf{x}}$	Kelly (1987,1989); $P = M \Rightarrow$ unknown deterministic target, Reed-Yu (1990)	$P = 1 \Rightarrow$ GLRT $P = M \Rightarrow$ $T(\mathbf{x}) = \mathbf{x}^T\bar{\mathbf{R}}^{-1}\mathbf{x}$ Simplicity $\Rightarrow$ $\mathbf{S} \equiv \mathbf{I}_M$
$\mathbf{R} = \sigma_w^2\mathbf{I} + \sum_{k=1}^{Q}\mathbf{z}_k\mathbf{z}_k^T$ structured interference	$\mathbf{s} = a\mathbf{s}_t$	$\boldsymbol{x}$ = test measurement $\mathbf{S} \equiv [\mathbf{s}_1\ \mathbf{s}_2 \dots \mathbf{s}_P]$ $\mathbf{Z} \equiv [\mathbf{z}_1\ \mathbf{z}_2 \dots \mathbf{z}_Q]$	$\mathbf{S} = \mathbf{s}_t \Rightarrow$ $\hat{a} = \dfrac{\mathbf{s}_t^T\mathbf{P}_Z^{\perp}\mathbf{x}}{\mathbf{s}_t^T\mathbf{P}_Z^{\perp}\mathbf{s}_t}$	Classical F-test for linear statistical models; OSP: Harsanyi-Chang (1994)	Orthogonal subspace projection (OSP): $T(\mathbf{x}) = \mathbf{s}_t^T\mathbf{P}_Z^{\perp}\mathbf{x}$
	$\boldsymbol{s} = \sum_{k=1}^{P} a_k \boldsymbol{s}_k = \boldsymbol{Sa}$ $1 \le P \le M$		$T'(\mathbf{x}) = \dfrac{\mathbf{x}^T\mathbf{P}_Z^{\perp}\mathbf{P}_G\mathbf{P}_Z^{\perp}\mathbf{x}}{\mathbf{x}^T\mathbf{P}_Z^{\perp}\mathbf{P}_G^{\perp}\mathbf{P}_Z^{\perp}\mathbf{x}}$ $\mathbf{P}_G \equiv \mathbf{G}(\mathbf{G}^T\mathbf{G})^{-1}\mathbf{G}^T$ $\mathbf{G} \equiv \mathbf{P}_Z^{\perp}\mathbf{S}$ $\mathbf{P}_G^{\perp} \equiv \mathbf{I} - \mathbf{P}_G$	Classical F-test for linear statistical models; Signal processing interpretations Matched Subspace Detector (MSD), Scharf-Friedlander (1994)	$T(\boldsymbol{x}) = \dfrac{T'(\boldsymbol{x}) / P}{M-P-Q}$

Hyperspectral Detection Results

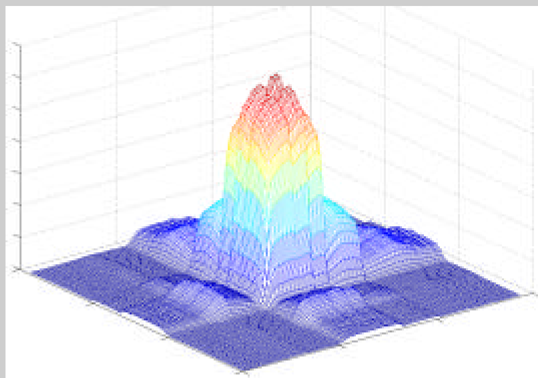


- **HYDICE (HYperspectral Digital Imagery Collection Experiment)**
  - **Airborne sensor**
- **210 spectral bands**
  - **399-2501 nm**
  - **Channel widths ~ 3 – 11 nm**
  - **Spatial resolution, 1m x 1m**
- **Look for sub-pixel targets**

Mean Target/Tree Spectra



Covariance for Trees



Comparative Detector Performance

Sub-pixel Targets

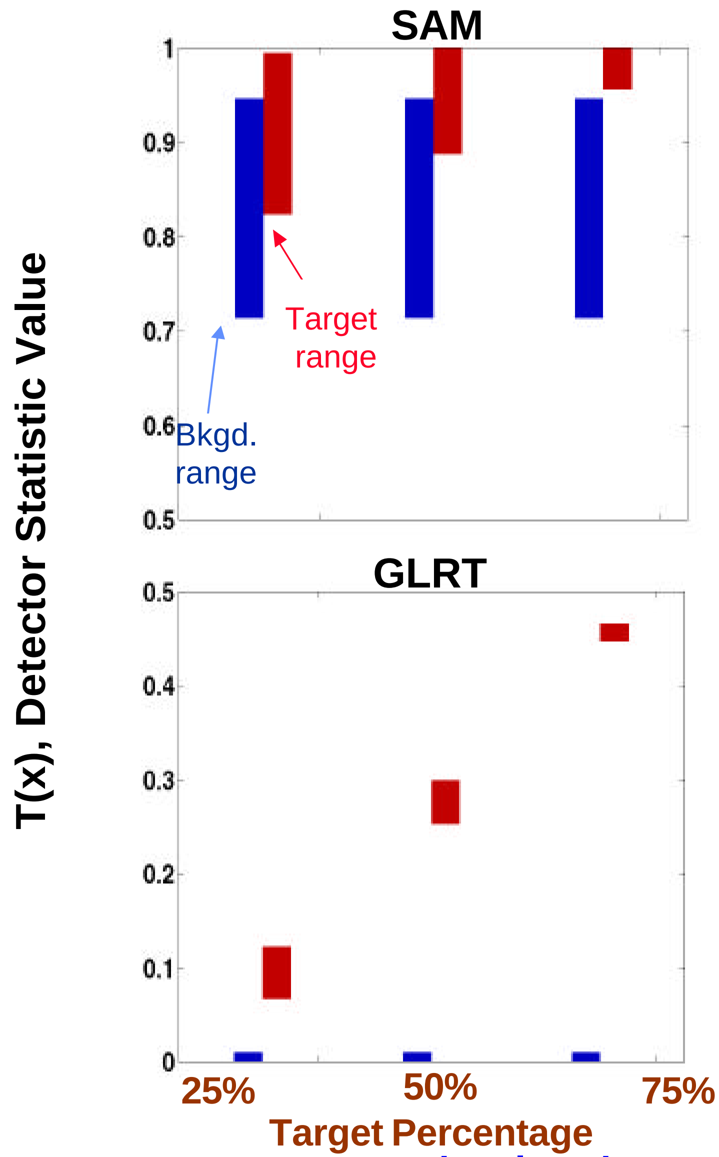
- 8232 tree pixels
- 8232 synthetic mixed pixels
  - 25% / 75%
  - 50% / 50%
  - 75% / 25%
- Two detectors
  - SAM ("unwhitened")

$$T_{SAM}(\mathbf{x}) = \frac{(\mathbf{s}^T \mathbf{x})}{\sqrt{(\mathbf{s}^T \mathbf{s})}\sqrt{(\mathbf{x}^T \mathbf{x})}}$$

  - GLRT

$$T_{GLRT}(\mathbf{x}) = \frac{(\mathbf{s}^T \overline{R_b}^{-1} \mathbf{x})^2}{(\mathbf{s}^T \overline{R_b}^{-1} \mathbf{s})(1 + \mathbf{x}^T \overline{R_b}^{-1} \mathbf{x})}$$

  - Measure range of test statistics



Conclusions

- Under LMM, hyperspectral sensing shares a common signal model with MTI radar
  – Endmembers « Steering vectors
  – Abundances « RCS
- Hyperspectral processing has leveraged optimal detection algorithms from radar
  – Exploit spectral differences between targets and background
- Successful sub-pixel target detection depends upon
  – Target/background subspace relationship
  – Fraction of target present