KASSPER Conference
April 2004

A Knowledge-Aided STAP Architecture

W.L. Melvin, Ph.D., and G.A. Showman, Ph.D.

Georgia Tech Research Institute (GTRI)

Sensors & Electromagnetic Applications Laboratory

bill.melvin@gtri.gatech.edu, Ph. 770-528-3274

Outline

- Heterogeneous, nonstationary clutter
  - Definitions, impact on STAP, numerical examples
- Prioritizing the challenge
  - Architecture drivers
- Proposed KA-STAP architecture
- Knowledge-aided prediction/estimation
  - Discussion of components, calibration requirements, application to simulated data
- Overview of discrete matched filtering
- Training strategies and requirements
- Constrained adaptive processor
- Other implementation considerations
- Summary

Objective: Impact Next Generation Radar

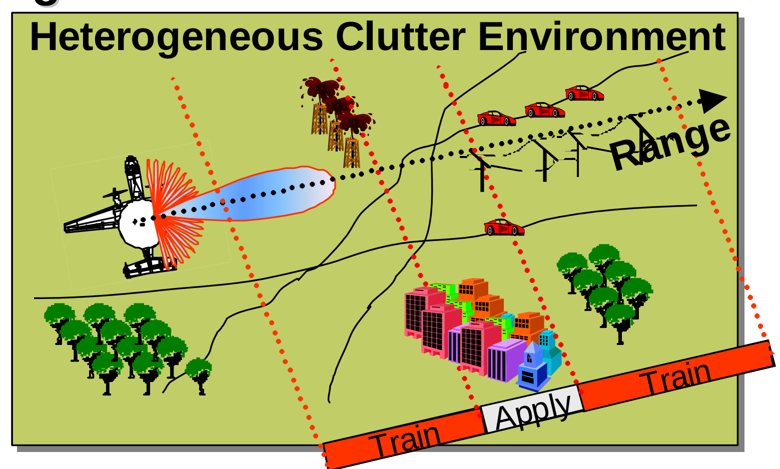
- Detecting slow moving targets in the presence of clutter and jamming (endo-clutter detection) is paramount
- STAP is critical technology, supports high area coverage rate (ACR) and overcomes diffraction-limited performance
- Minimum detectable velocity (MDV) and ACR are key metrics, *but detecting and tracking high-priority targets also critical*
- GMTI radar must operate effectively in complex, heterogeneous clutter environments and *provide "cradle to grave" tracking capability*

Estimating critical parameters in heterogeneous environments

$$SINR = SNR \times \underbrace{\left(\frac{SINR_o}{SNR}\right)}_{L_{s,1}} \times \underbrace{\left(\frac{SINR_{a/iid}}{SINR_o}\right)}_{L_{s,2}} \times \underbrace{\left(\frac{SINR_{a/het}}{SINR_{a/iid}}\right)}_{L_{s,3}}$$

$\mathbf{R}_k = \text{known}$

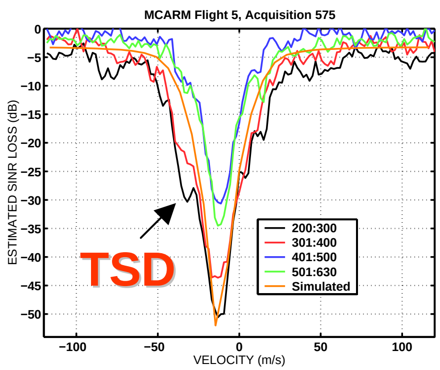
iid $\times$ heterogeneous



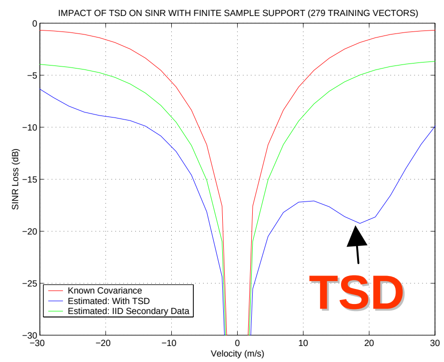
What is Heterogeneous Clutter (Revisited)?

Targets-in-Secondary Data (TSD) -- #1

Measured

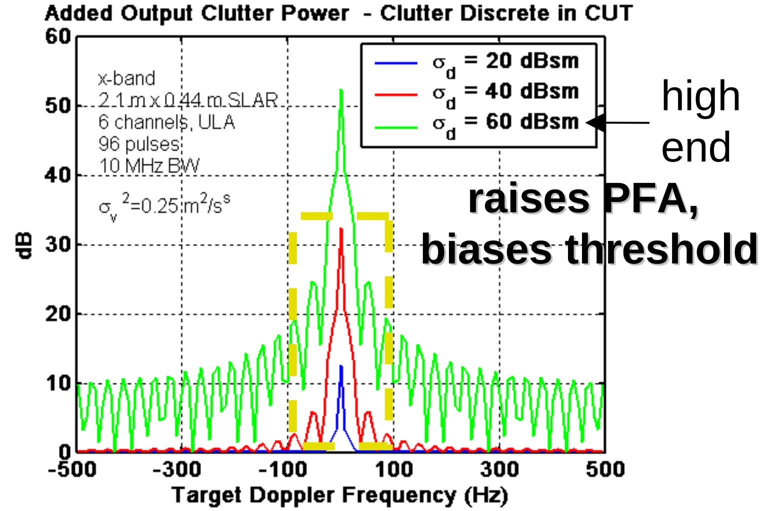


Simulated

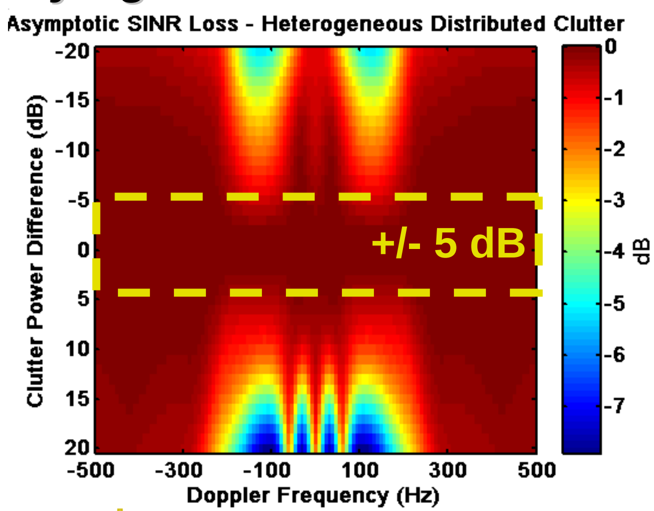


*** L-band measured and simulated**

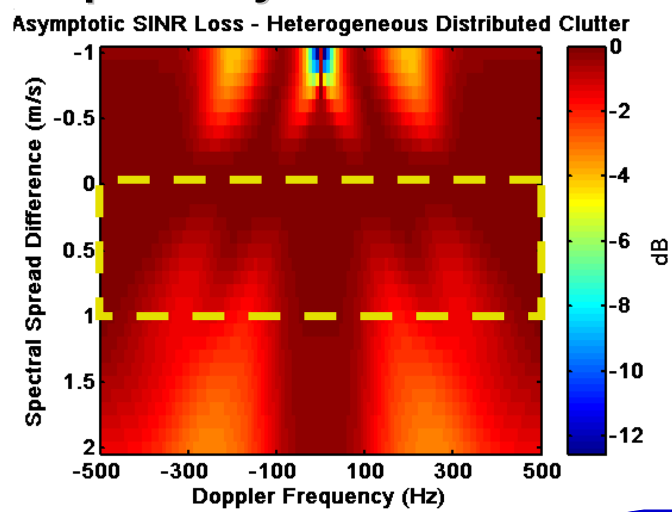
Clutter Discretes – #2



Varying Distributed Clutter – #3



Spectrally Mismatched – #3



*** #2, #3's: x-band, 2.1 m x 0.44 m SLAR, 6 channels, Np=96, varVSC = 0.25 (unless noted)**

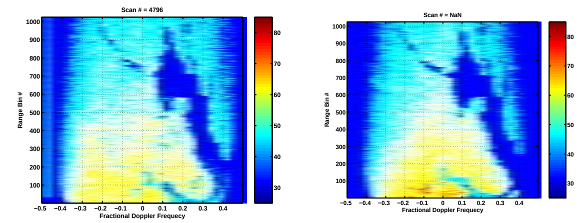
Georgia Tech Research Institute

What's Predictable? What's Not?

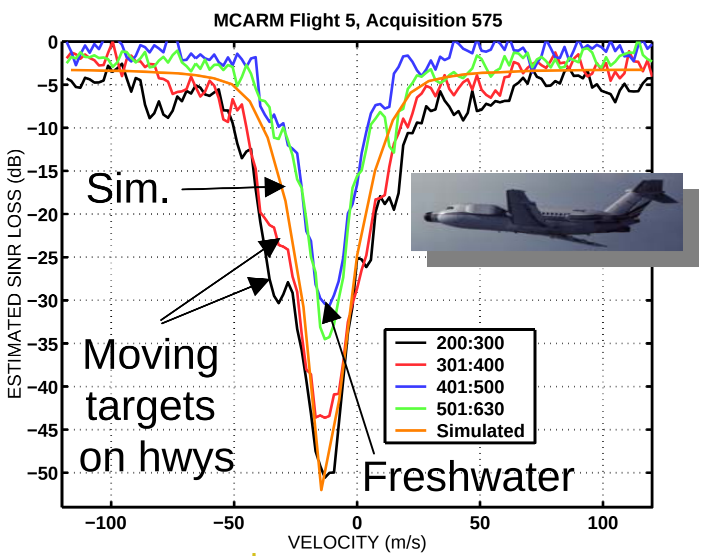
- Clutter Doppler response predictable
- Clutter angular response, tied to Doppler, predictable but requires knowledge of array normal and manifold
- Distributed clutter amplitude partially predictable
- Clutter spectral characteristics difficult to predict
- Complex system response – e.g., array errors, radome and near-field scattering – difficult to predict

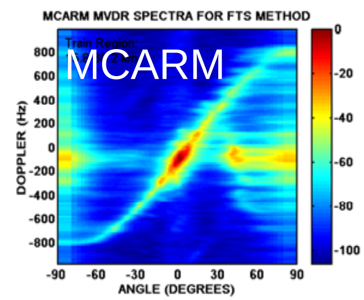
NORTHROP GRUMMAN
Electronic Systems

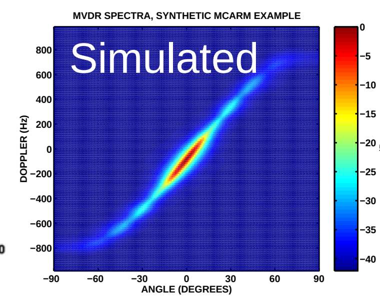
Measured FOPEN **Simulated** FOPEN

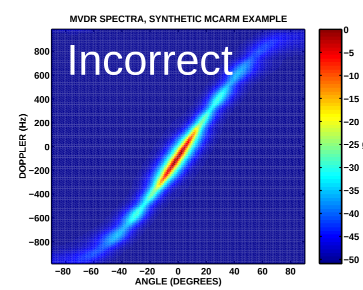


* FOPEN data is property of Northrop-Grumman Corp









Requirements:
- Precise knowledge of platform velocity vector
- Platform pitch, roll and yaw
- Measured array normal

Errors in knowledge or model are critical

KA Signal Processing

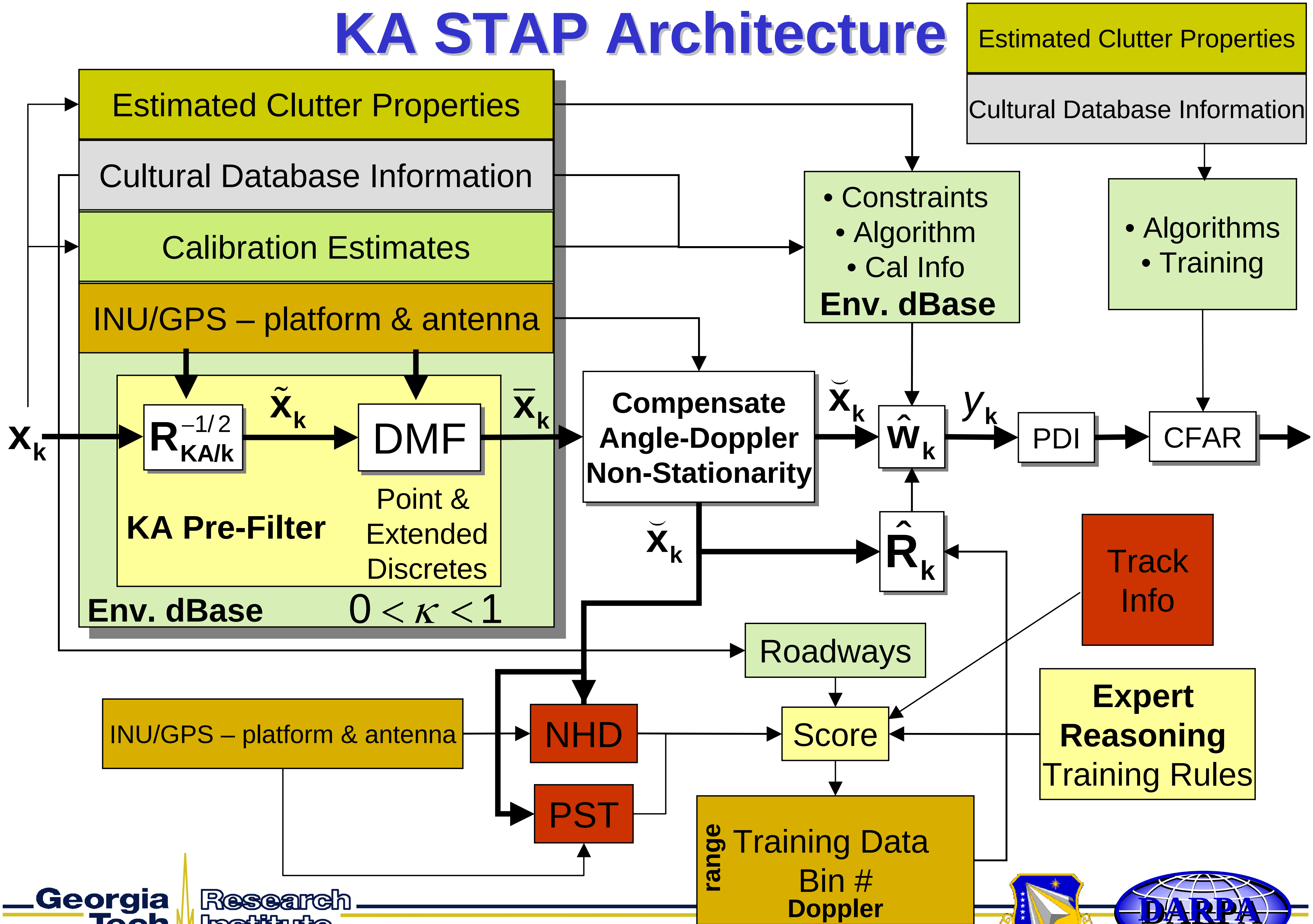
- Knowledge-aided signal processing…
  - Aggregates information from observations and other data sources (in an environmental data base)
  - Hypothesizes multiple, possible models and determines "best fit"
  - Gathers evidence to substantiate hypotheses
  - Provides feedback to adjust system response
  - Captures expert reasoning in decision-making process
  - Adapts reasoning and implementation to dynamics of environment

$\kappa =$ Fraction of *a priori* knowledge

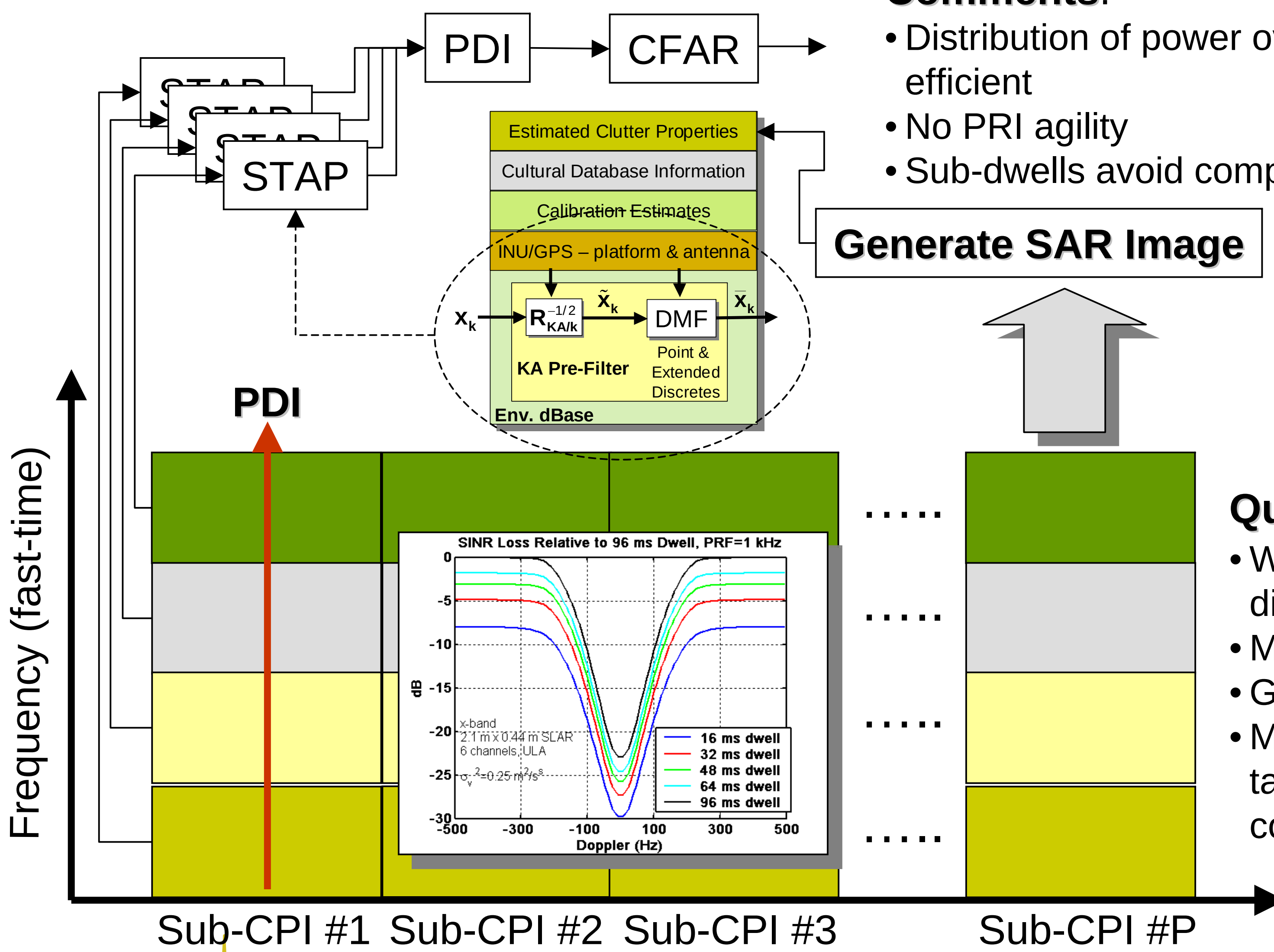
$\kappa = 0$ | $\kappa = \varepsilon;\ \ 0 \le \varepsilon \le 1$ | $\kappa = 1$

Traditional STAP	KA-STAP	Knowledge-Only STP
Measurements $\Rightarrow$ $\hat{\mathbf{R}}_k$	Measurements + Predictions	Predictions $\Rightarrow$ $\mathbf{R}_{k/PW}$

KA STAP Architecture



Mode Change: Processing Timeline



slow-time

Comments:

- Distribution of power over frequency less efficient
- No PRI agility
- Sub-dwells avoid complex Tgt phs history

Uses:

- Generate non-causal response
- Detect high-priority, time critical targets
- Image mover?!

Questions:

- Where to excise discretes?
- MDV advantages?
- Gain against TSD?
- Maximum dwell before target phase history too complex? (res. scaling)

Georgia Tech Research Institute

Knowledge-Aided Prediction/Estimation (KAPE) Steps

(1) Determine array normal

(2) Estimate array manifold

(3) Remove strong discretes

(4) Estimate distributed clutter power

  Variety of approaches: beamforming, Doppler filtering (like SAR), and super-resolution (smooth over snapshot)

(5) Form pre-filter(s) over angular limits using INU/GPS, DEM, and results from (4)

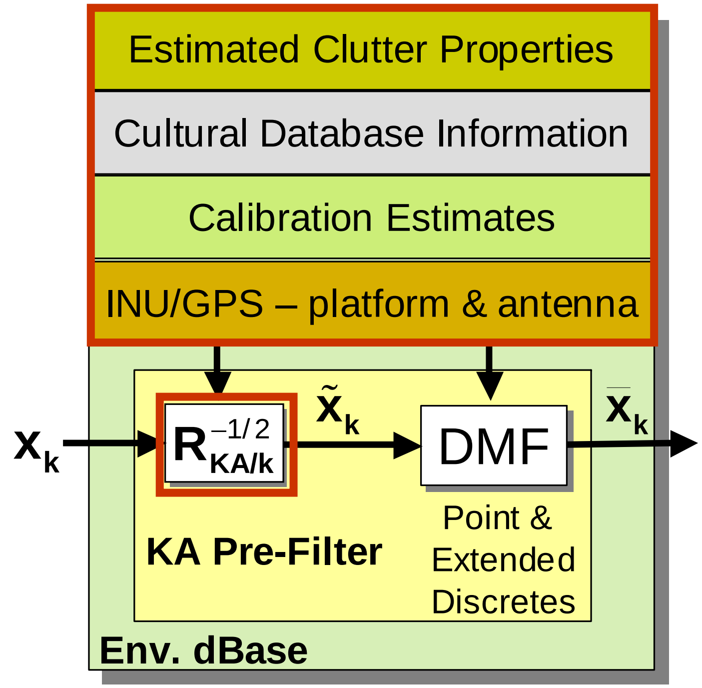
(6) Estimate spectral spread

(7) Ascertain performance (or, aggregate evidence)

(8) Iterate filter design

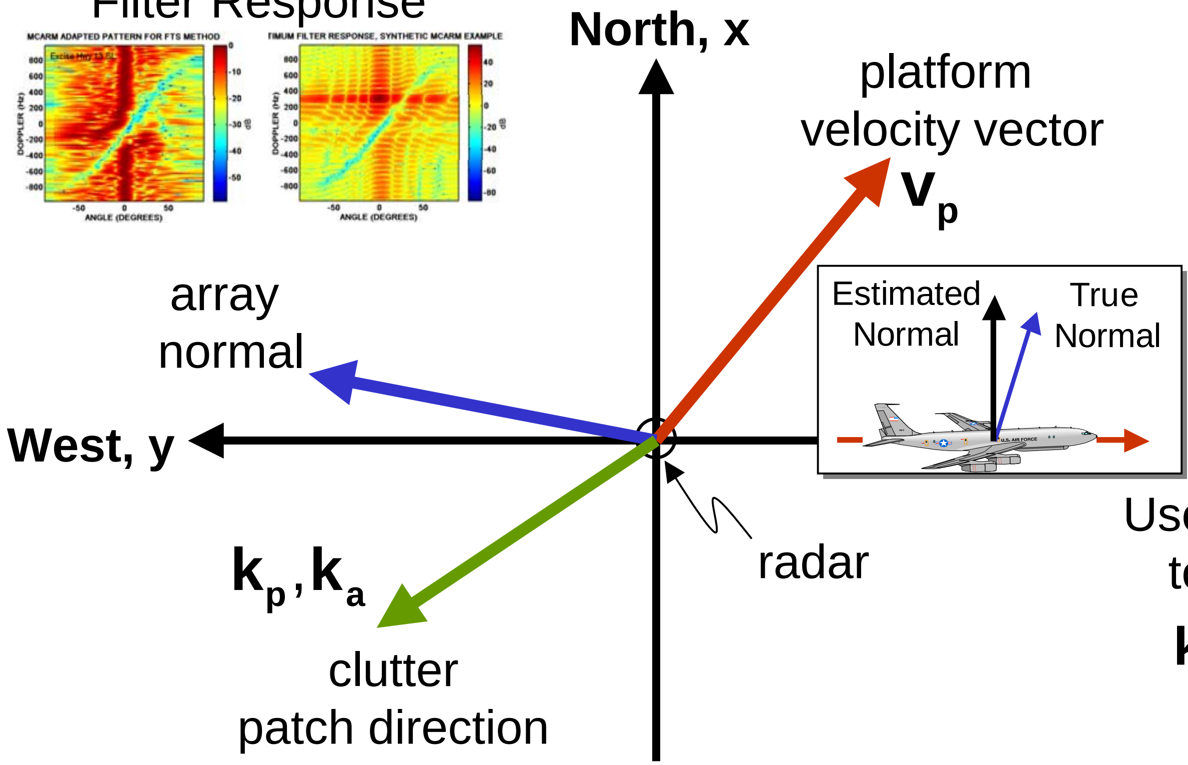
  "Quick" solutions: interpolation, limited angular extent

  Do this in parallel



Mapping Spatial Wavenumber Vector to True North Direction Vector

Filter Response



Temporal steering vector

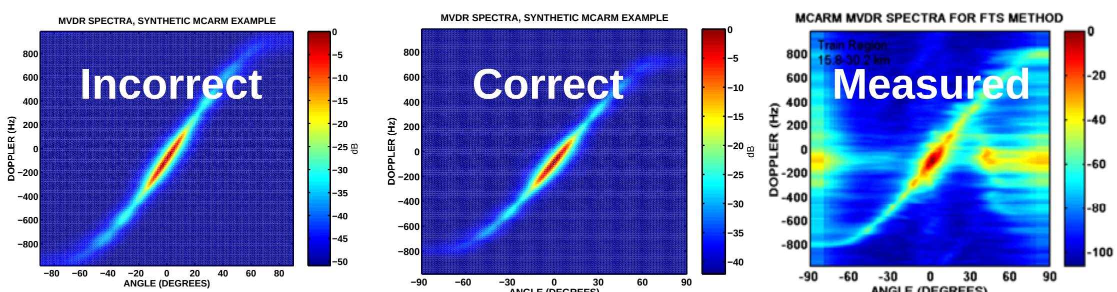
$$\mathbf{s_t} = \left(e^{j2\pi\left(\frac{2}{\lambda}\mathbf{k_p}\cdot\mathbf{v_p}\right)} \right)_{m=1}^{N}$$

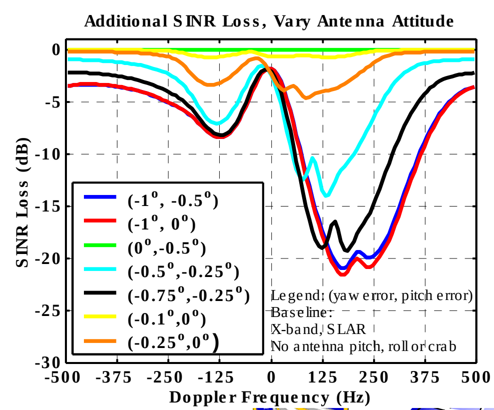
Spatial steering vector

$$\mathbf{s_s} = \left(e^{j\frac{2\pi}{\lambda}\mathbf{k_a}\cdot\mathbf{d_m}} \right)_{m=1}^{M}$$

Use knowledge-derived information to determine linear transform…

$$\mathbf{k_p} = \mathbf{T}^{-1}_{\mathbf{rcs\text{-}2\text{-}acs}}\mathbf{M_{yaw}}\mathbf{M_{pitch}}\mathbf{M_{roll}}\mathbf{k_a}$$



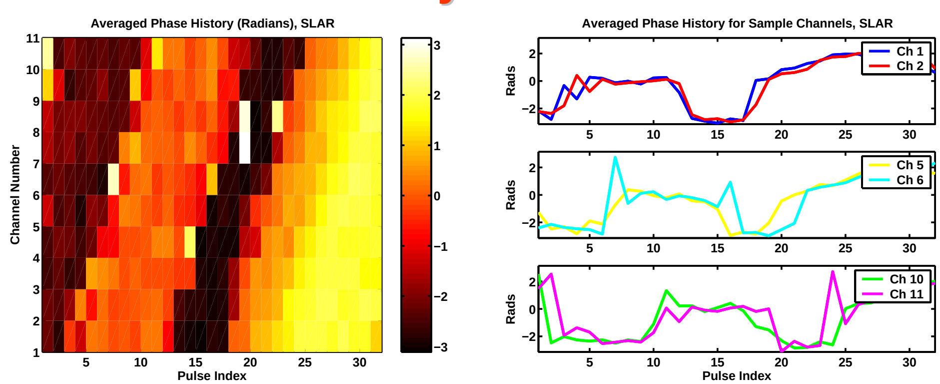


Georgia Tech Research Institute

Estimating Array Manifold

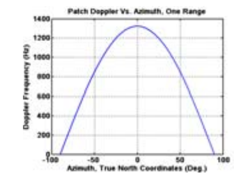
Method	Premise	Comments
Max. eigenvector, Doppler Centroid	Boresight clutter maximally projects onto max. eigenvector	Eigenvector spans multiple space-time signals, performance poor
Max. eigenvector, spatial covariance	Same premise as above, average over fast- and slow-time	Eigenvector spans multiple space-time signals, performance poor
X-corr. adjacent channel pairs	Adjacent channels exhibit max. overlap in data record	Performance improves as dwell increases
De-trend adjacent channel range-Doppler response	Exploit nominally linear phase between channels over Doppler, non-zero intercept is error	Requires Doppler centroid, performance often very good

Phase History for Short Dwell

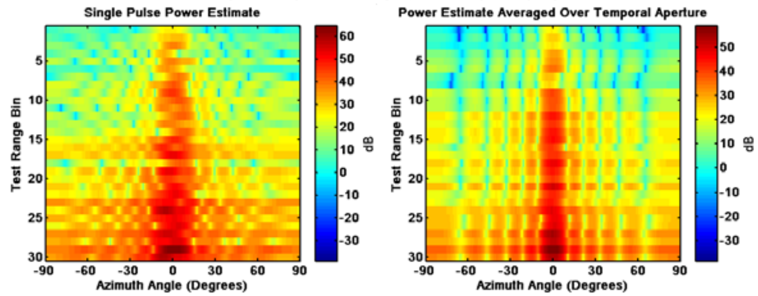


See App. 2 for further discussion…

Generating Pre-Filter



Power Estimates



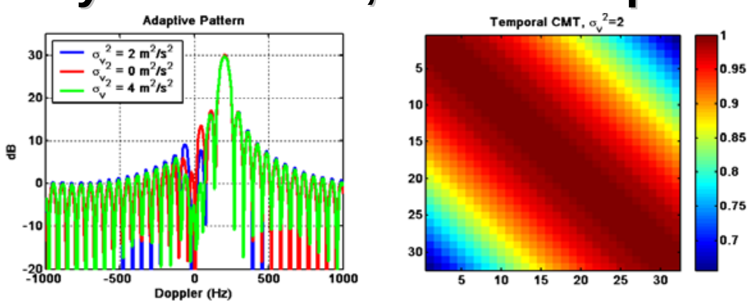
$$\mathbf{R}_{\mathbf{c/k}} = \mathbf{SPS}^{H}; \quad \mathbf{S} = \text{ calibrated steering matrix;}$$

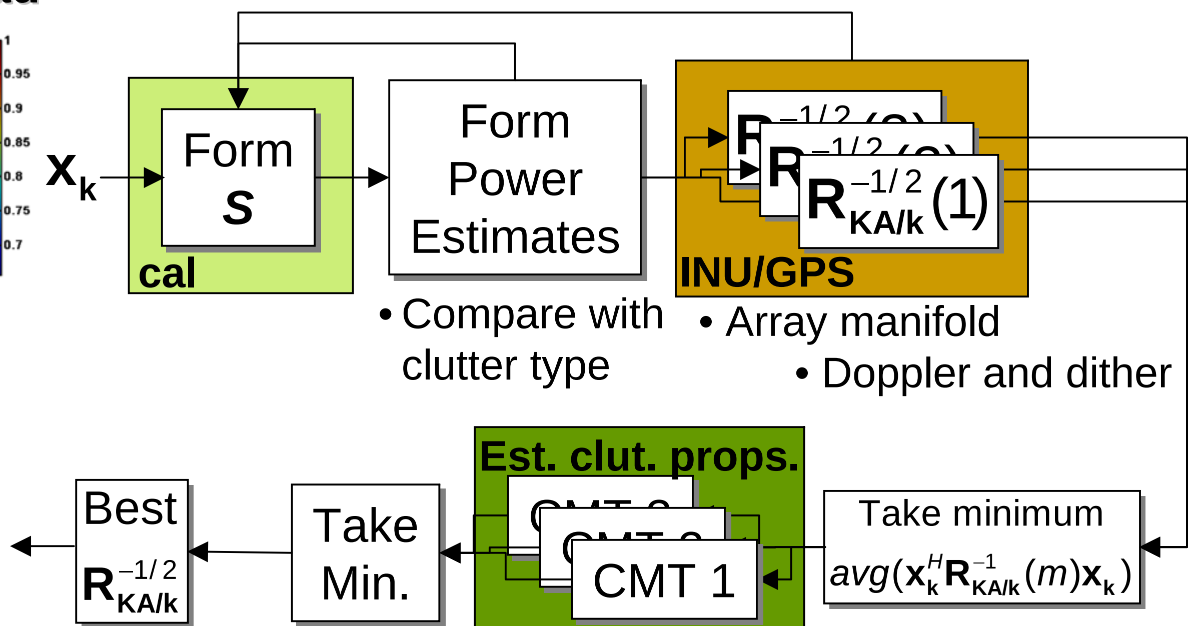
$$\mathbf{P} = \text{ diagonal clutter power matrix}$$

$$\mathbf{R}'_{\mathbf{c/k}} = \left(\mathbf{C}_{\mathbf{cmt\_t}} \otimes \mathbf{C}_{\mathbf{cmt\_s}}\right) \odot \mathbf{R}_{\mathbf{c/k}} \Rightarrow \mathbf{R}_{\mathbf{KA/k}} = \mathbf{R}'_{\mathbf{c/k}} + \mathbf{R}_{\mathbf{n}}$$

* Can make CMT angle dependent

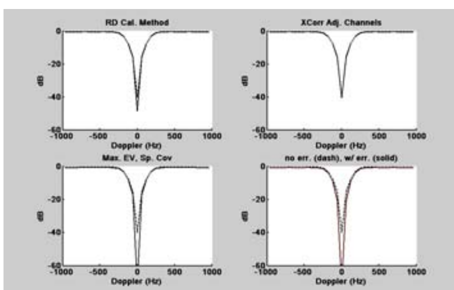
Physical model, estimate spread





- Compare with clutter type
- Array manifold
  - Doppler and dither
- Compare spread with clutter type

Estimate array characteristics



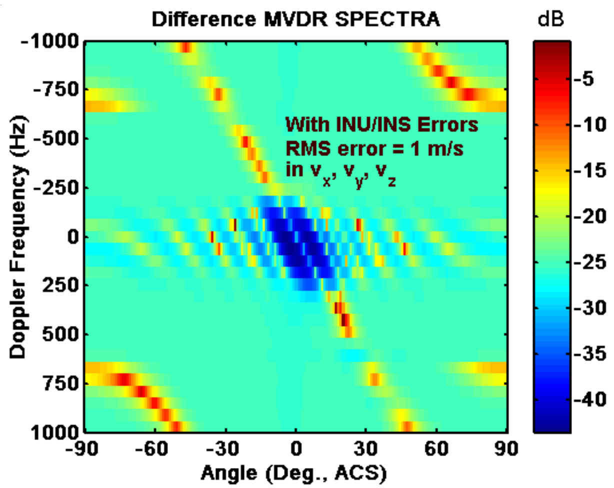
Key Factors

- Slope
- Calibration
- Amplitude
- Spectral width

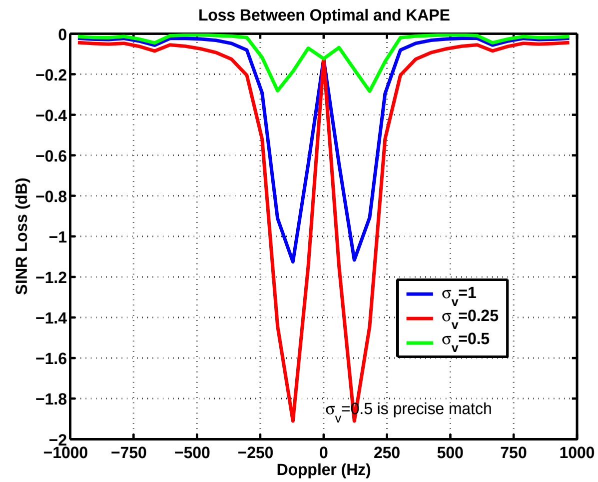
Georgia Tech Research Institute

KAPE Performance: L-Band Example

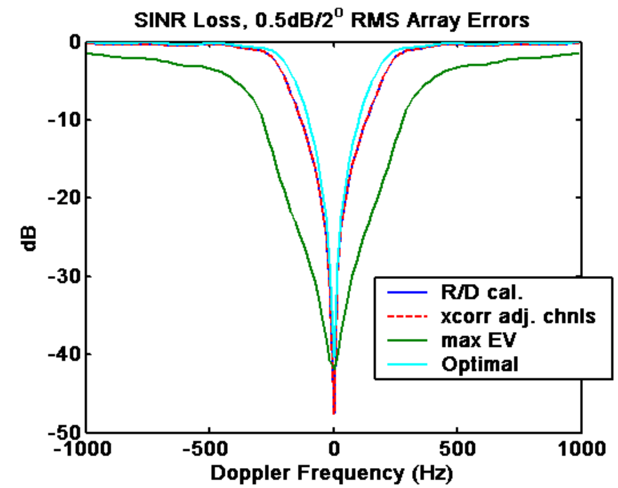
INU Errors

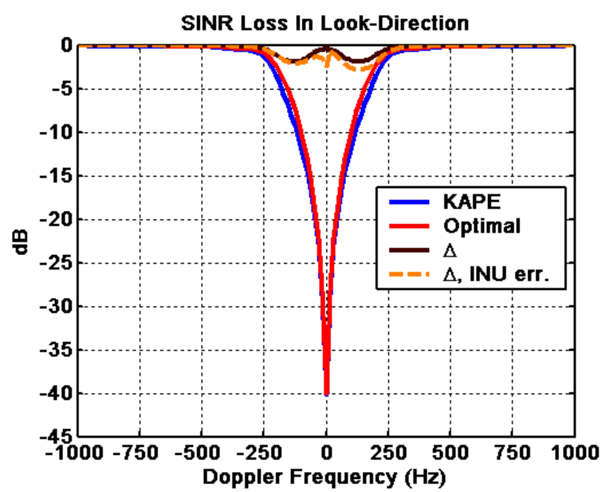


Spectral Mismatch

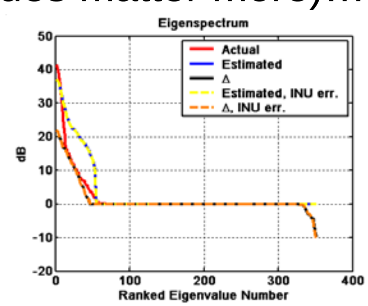


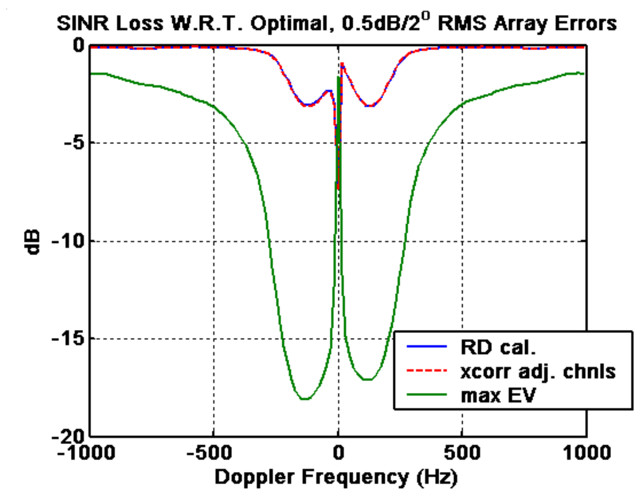
Array Errors & Cal.





Eigenspectra doesn’t give directional info (some eig. values matter more)…

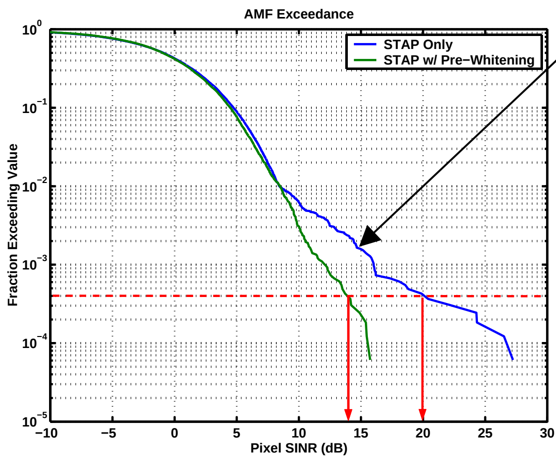




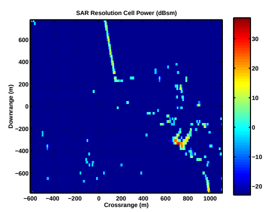
Georgia Tech Research Institute

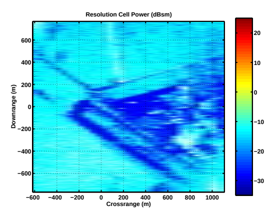
DMF Re-Visited

When and how to remove discretes?

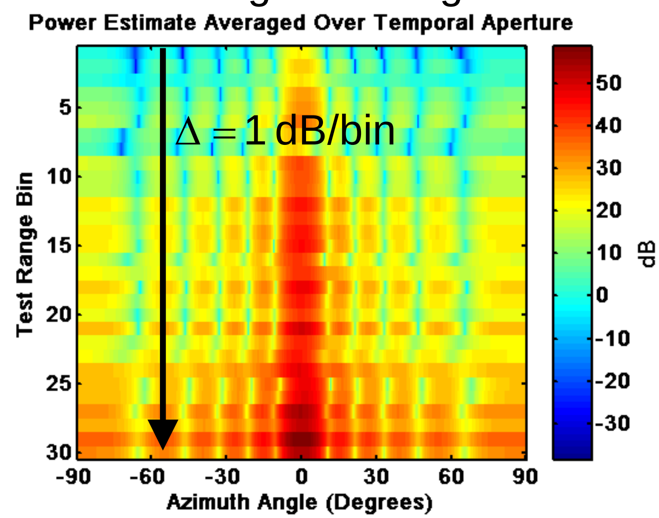


- Heavier tail due to discretes
- Threshold increase to maintain P_{FA}

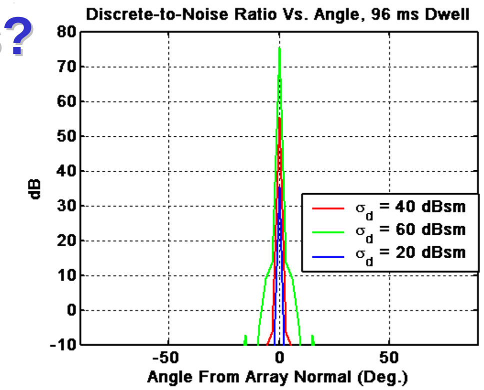


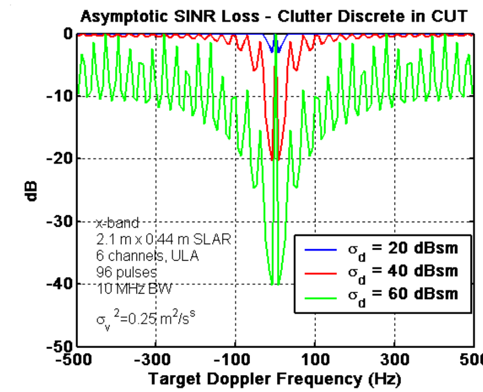


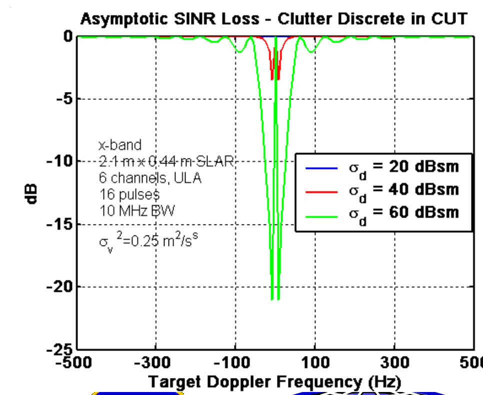
KAPE tracks power change over rng



More problematic at higher res.







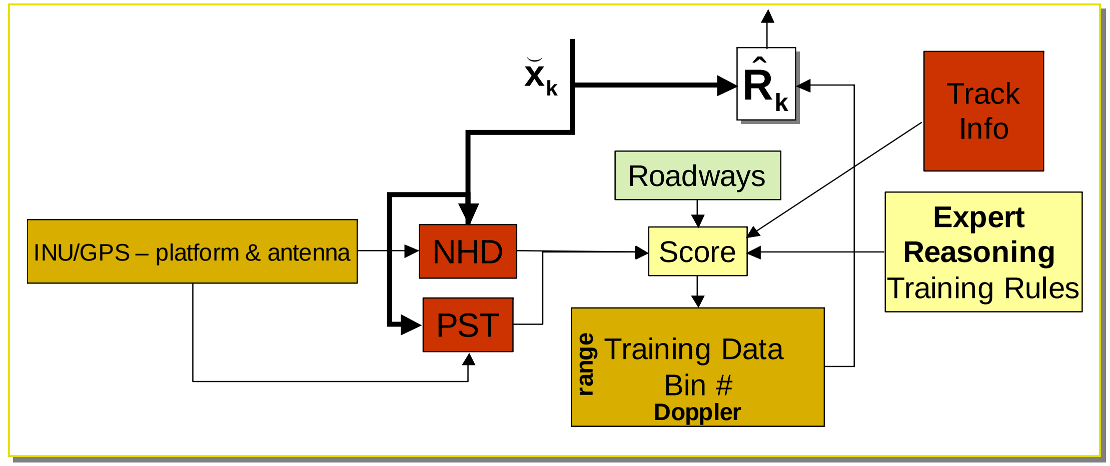
Approaches:

- CLEAN and decimate long dwell data
- Use KAPE
- Incorporate some fraction of discrete in training data
- Post-detection logic/CLEAN AMF

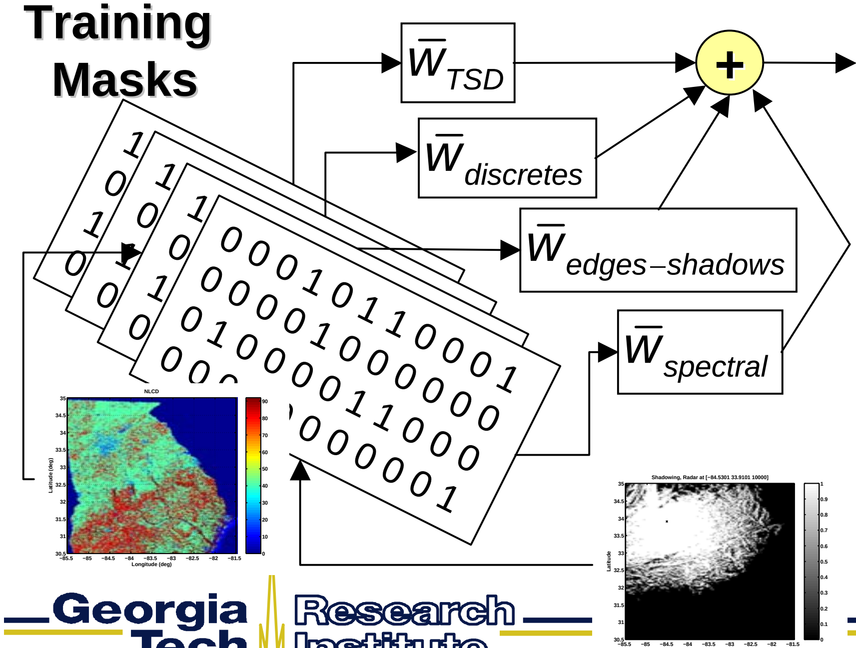
Training Strategies

Training Objectives:

1) Remove TSD (modified NHD, track info)
2) Mitigate clutter residue leading to increased P_{FA} (constrained PST)
3) Prevent overnulling leading to signal cancellation (data screening)
4) Incorporate “expert reasoning,” based on analysis of key baseline scenarios, into sample selection strategy



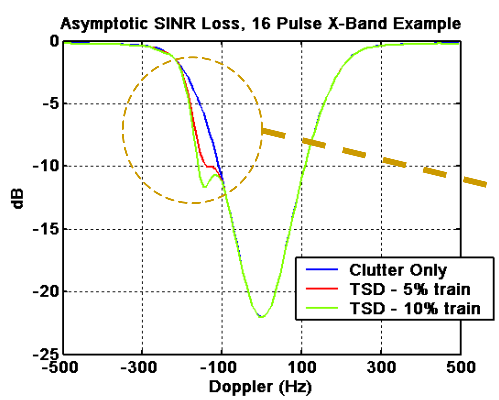
Training Masks



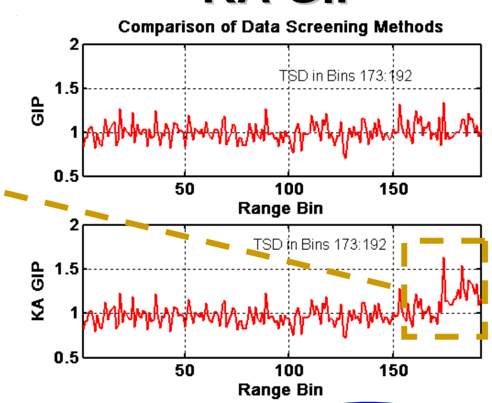
Training Score

7	0	0	0	0	9	2	0	0	0	0
0	0	0	2	1	0	0	0	8	0	0
1	1	0	0	0	2	0	0	0	0	0
0	0	1	0	3	0	0	3	0	0	1

$$\hat{\breve{\mathbf{R}}}_k = \left(\sum_{m=1}^{P} a_m\right)^{-1} \sum_{p=1}^{P} a_m \breve{\mathbf{x}}_k \breve{\mathbf{x}}_k^H$$

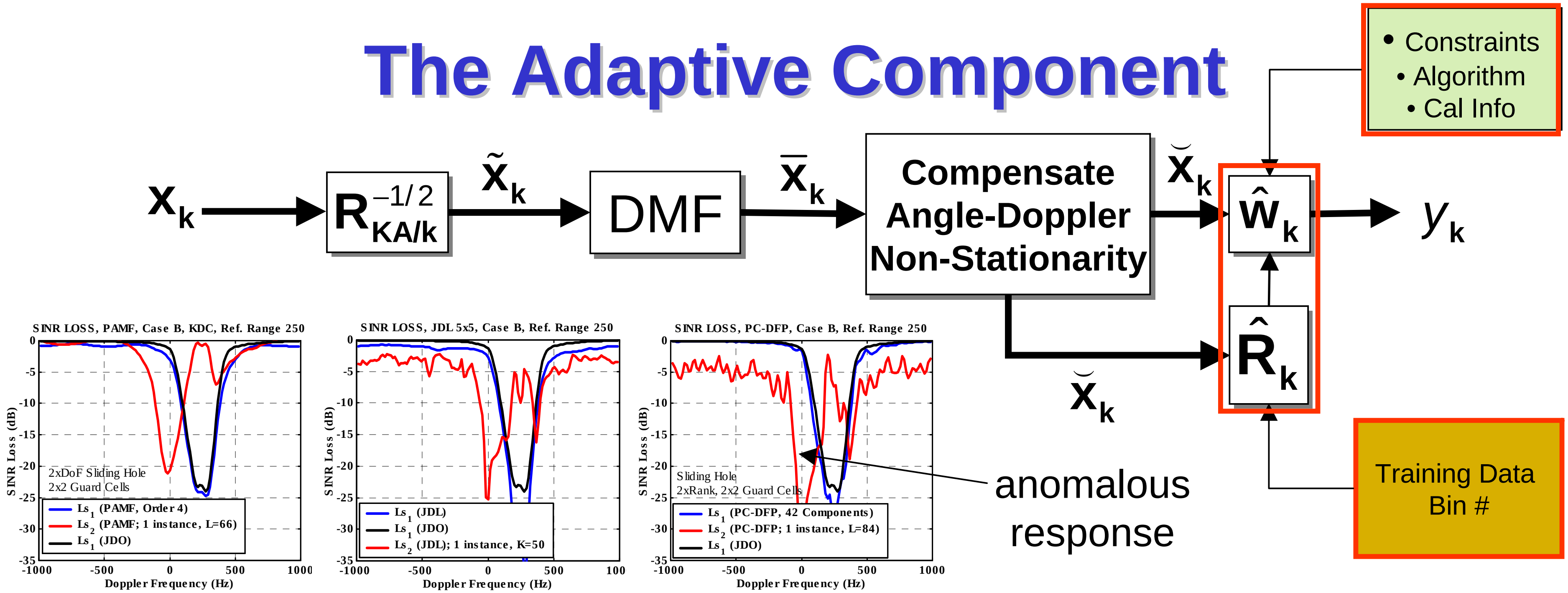


KA GIP



- target yields SNR_i=20 dB
- uses our previous x-band ex

The Adaptive Component



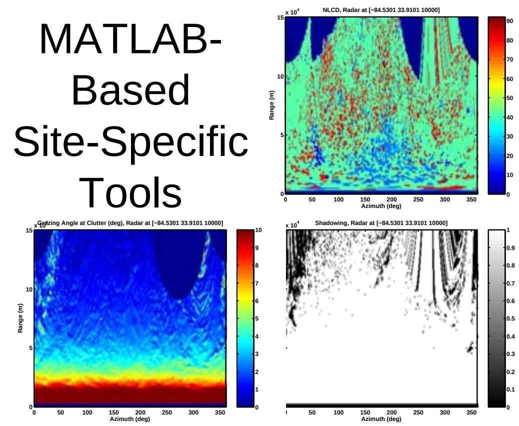
- Adaptivity employed to remove any correlated residual
- Adaptivity necessary when jamming present (removing strong clutter beneficial)
- Training is critical (avoid TSD, pre-filter stages ideally afford TSD-to-clutter enhancement)
- Constraints can include pre-adaptive nulls applied to regions of high reflectivity (Good calibration necessary to implement constrained beamformer)
- Post-Doppler techniques preferred, easier to train
- Important when KA applied only over limited regions, or when quality of knowledge questionable (especially calibration information)

Georgia Tech Research Institute

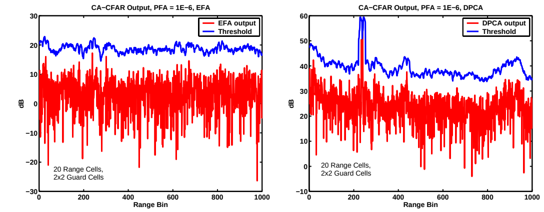
Additional Implementation Considerations

- How best to employ and queue site-specific tools?
  - Identify impending challenges
    - Regions rich in clutter discretes or TSD
  - Compare estimated and anticipated results
- Developing “adaptable” expert rules, especially for training and constrained filtering
  - “Learning” from sorties
- Determining “goodness” of implementation, iterating as necessary
- Implementing the best threshold setting

MATLAB-Based Site-Specific Tools



Threshold setting still requires care…



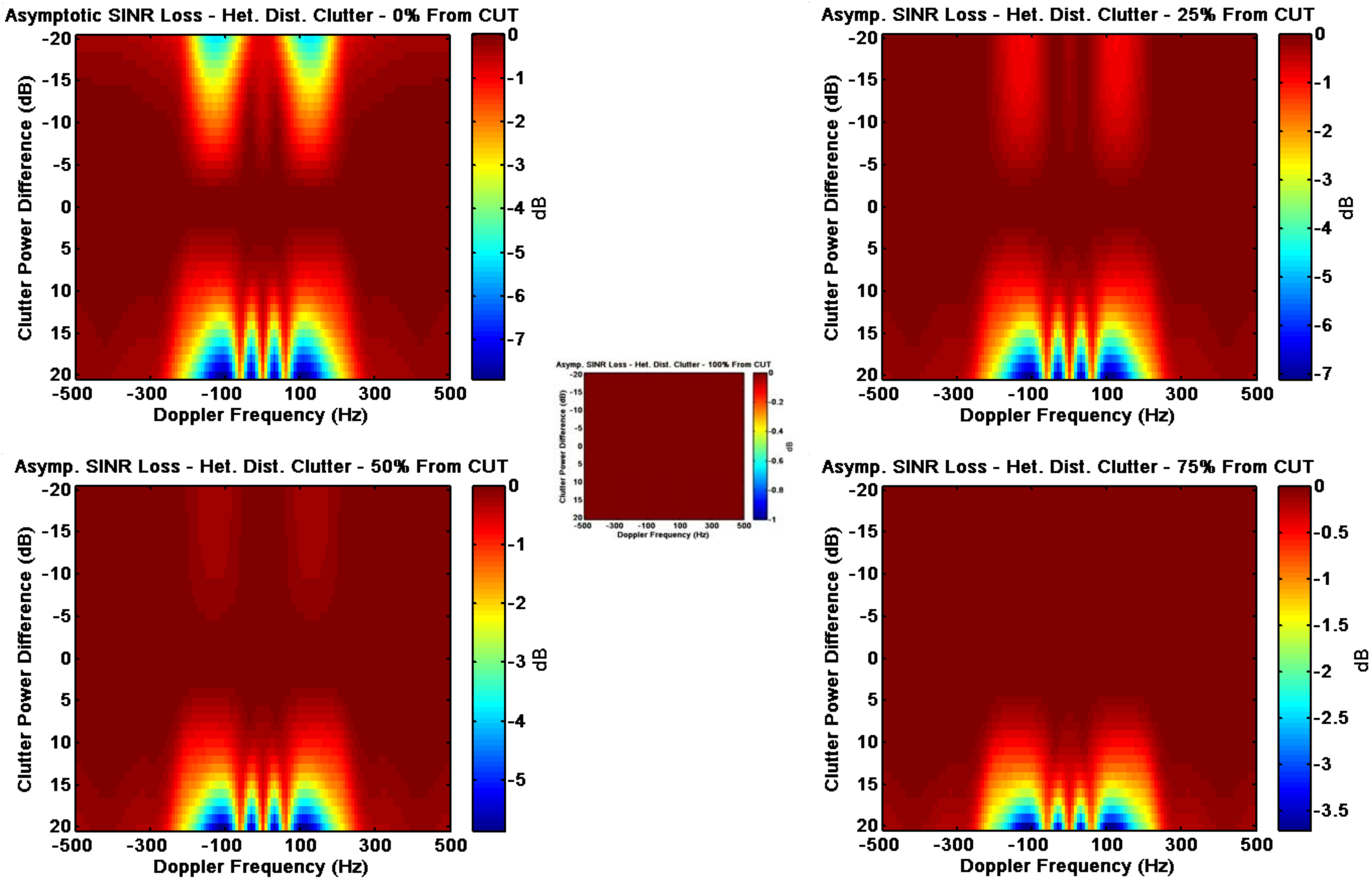
Georgia Tech Research Institute

DARPA

Summary

- KA STAP involves…
  - Aggregating information from observations and other data sources
  - Hypothesizing plausible models for observed data
  - Testing veracity of models
  - Iterating (real-time!) design as necessary
- Proposed KA STAP architecture incorporates preceding elements
  - KAPE: estimating angle-Doppler response using INU/GPS, power estimates, calibration, array normal estimation, conditioned on expected values determined using data base, iterating via filter bank design and feedback
  - DMF: determining mode based on data base, scanning data for discretes, employing anticipated impulse response to deconvolve data, removing discretes
  - Adjusting for clutter non-stationarity using a priori knowledge
  - Expert reasoning applied to training step of adaptive stage
- Showed numerical examples rationalizing different steps
- Future work will involve integrating, testing and enhancing the whole architecture

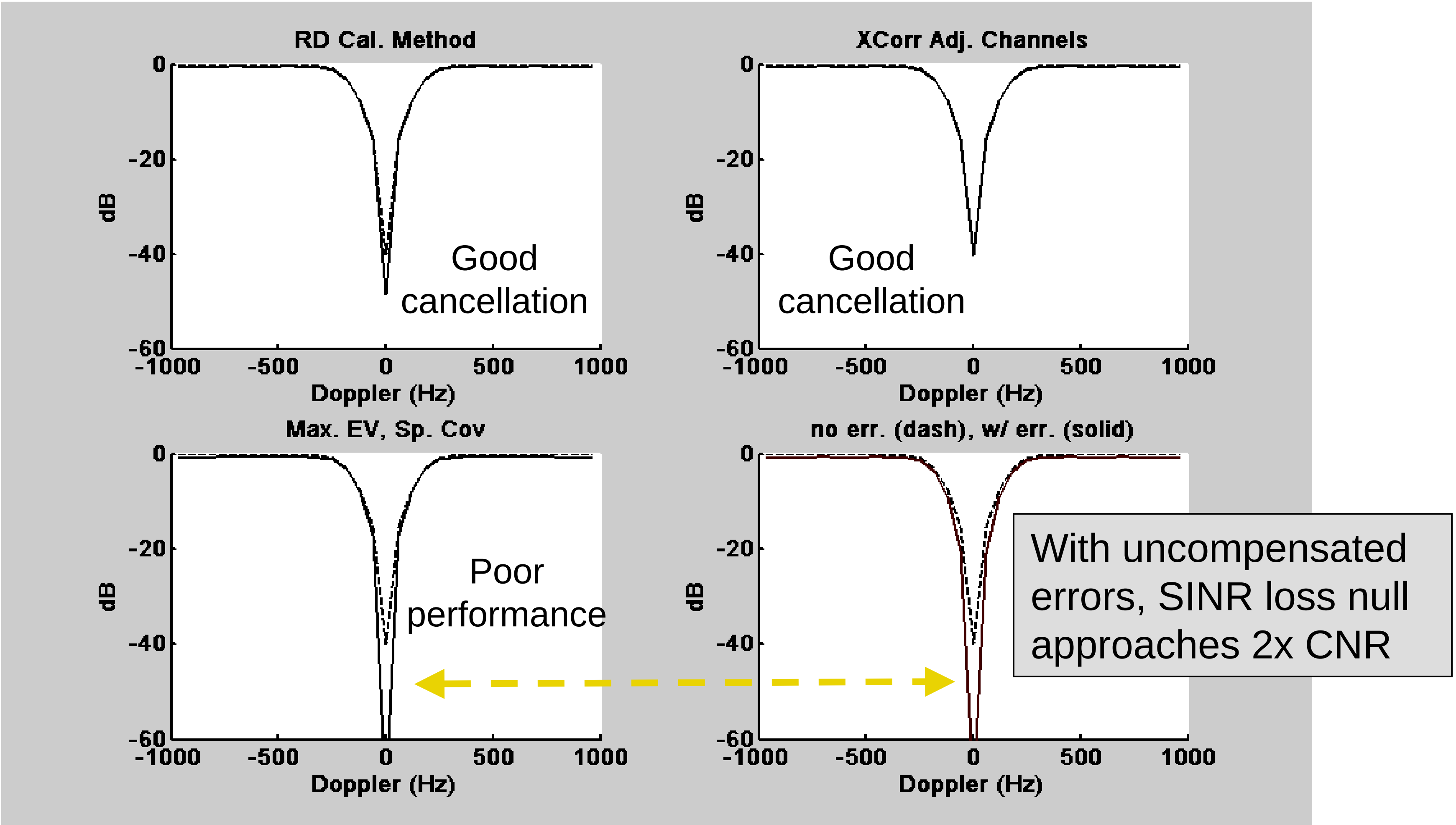
App. 1 - Heterogeneous Distributed Clutter



*** x-band, 2.1 m x 0.44 m SLAR, 6 channels, Np=96, varVSC = 0.25**

App. 2 – Comparison of CAL Methods

Range-Doppler and cross correlation methods yield very good performance



(dashed: error free; 0.5 dB/2º RMS errors at sub-array level)