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Knowledge-Aided Parametric Covariance Estimation (KAPE)

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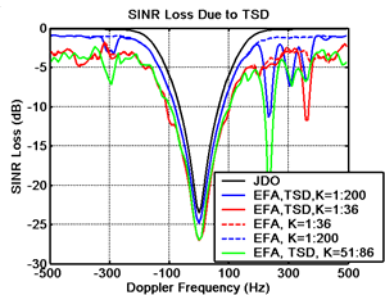
Outline

- Introduction
- Unique aspects of KAPE
- Signal modeling and validation
- KAPE implementation
- Implementation steps

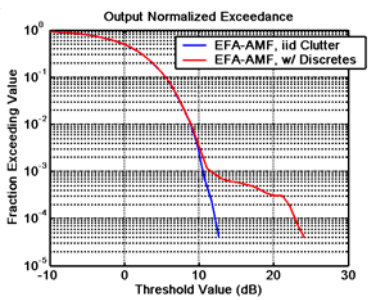
Specific Challenges

- Target-Like Signals in the Secondary Data (TSD)



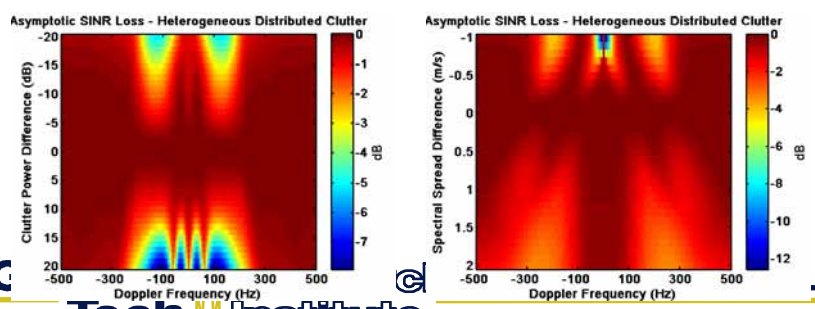
Reduces signal gain, affects variance of bearing estimate, distorts adaptive filter response, leads to inefficient allocation of adaptive DoFs

- Clutter Discretes



Increases false alarm rate (in CUT), can degrade output SINR and bias threshold (in training)

- Distributed Clutter Variations



Leads to degraded output SINR via two predominant mechanisms:

- Overnulling → signal cancellation
- Undernulling → increased clutter residue

Amplitude and spectral characteristics

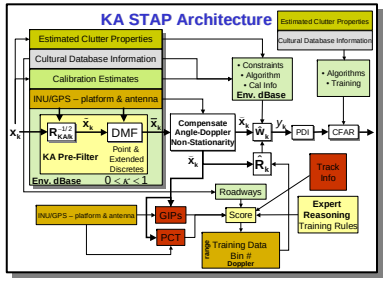
Site-specific clutter

Objectives

- Improve MTI radar performance in heterogeneous clutter environments by exploiting *a priori* knowledge
- Enhance front-end processing functionality by…
  - Removing bulk of clutter to increase contrast against outliers
  - Providing good instantaneous response by tracking clutter variation
  - Avoiding anomalous response due to targets-in-the-secondary data (TSD)
- Reduce higher-dimensional parameter estimation step to estimating several model parameters

Enforce filter response consistent with anticipated properties of clutter

GTRI KA-STAP Flow Diagram



M-Channel Data In

Array Manifold Estimation

Large Discrete Removal 3-D KA Clean

KAPE Clutter Pre-Whitening

Angle-Doppler Profile Alignment

Post-Doppler STAP

DOA Estimate Feature Calcs.

Post-Detection 2-D KA Clean

Detection Map

Clutter Discretes

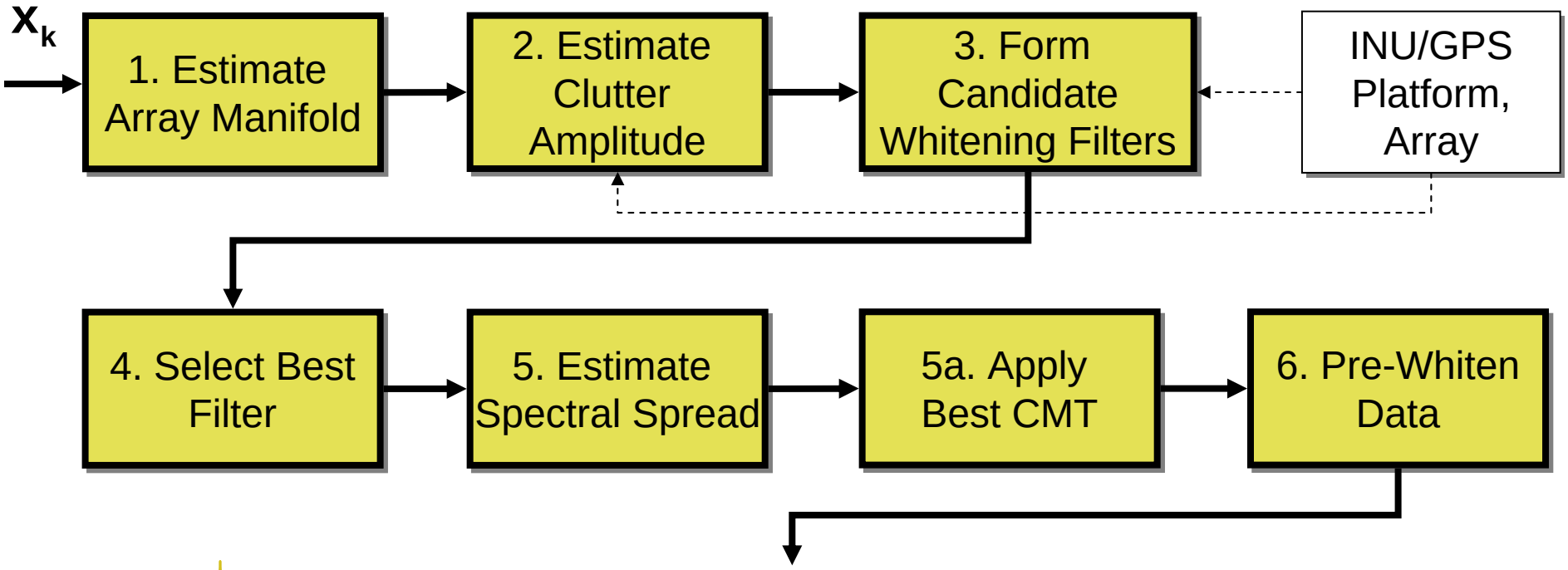
TSD

KA Training

* Details presented at QPR in Oct 2004

Knowledge-Aided Parametric Covariance Estimation (KAPE) Overview

- Exploit certain aspects of clutter known with fairly high accuracy to pre-whiten data
  - Blend both measurements and *a priori* knowledge
- **Goals**: (1) Avoid TSD; (2) Provide good instantaneous response; and, (3) Remove bulk of clutter to provide contrast against certain outliers



Colored Loading

- Approaches by ISL [1] and Alphatech [2] very similar
  - Involves adding a scaled, simulated clutter covariance matrix to covariance estimate along with diagonal loading term
    - ISL – unity power, then scale by CNR
    - Alphatech – multi-CPI estimate of reflectivity, rescale eigenvalues, retain subspace defined by covariance estimate
  - Stated goal: “Faster convergence,” to “improve detection performance in heterogeneous clutter environments”
- SAIC [3] has different approach
  - Chooses colored diagonal loading matrix to impart specific quiescent response
  - Faster convergence is still goal

1. J.S. Bergin, C.M. Teixeria, P.M. Techau, and J.R. Guerci, “Space-time beamforming with knowledge-aided constraints,” in *Proc. 2003 Adaptive Sensor Array Processing Workshop*, MIT Lincoln Laboratory, Lexington, Massachusetts, March 11-13, 2003.
2. D. Page, S. Scarborough, G. Owirka and S. Crooks, “Improving knowledge-aided STAP performance using past CPI data,” in *Proc. 2004 IEEE Radar Conf.*, Philadelphia, PA, 26-29 April 2004, ISBN No. 0-7803-8235-8.
3. J.D. Hiemstra, “Colored diagonal loading,” in *Proc. 2002 IEEE Radar Conf.*, Long Beach, CA, 22-25 April 2002, ISBN 0-7803-7358-8.

Enhanced Convergence Offered By CL-STAP

$$\tilde{\mathbf{x}} = \mathbf{R}_{\mathbf{CL}}^{-1/2}\mathbf{x}; \quad \tilde{\mathbf{v}} = \mathbf{R}_{\mathbf{CL}}^{-1/2}\mathbf{v}$$

$$y = \hat{\mathbf{w}}^H\tilde{\mathbf{x}} = \tilde{\mathbf{v}}^H\hat{\mathbf{R}}_{\tilde{\mathbf{x}}}^{-1}\mathbf{R}_{\mathbf{CL}}^{-1/2}\mathbf{x} = \mathbf{v}^H\mathbf{R}_{\mathbf{CL}}^{-1/2}\hat{\mathbf{R}}_{\tilde{\mathbf{x}}}^{-1}\mathbf{R}_{\mathbf{CL}}^{-1/2}\mathbf{x}$$

$$\hat{\mathbf{R}}_{\tilde{\mathbf{x}}}^{-1} = \left(\frac{1}{L}\sum_{m=1}^{L}\mathbf{R}_{\mathbf{CL}}^{-1/2}\mathbf{x}_{\mathbf{m}}\mathbf{x}_{\mathbf{m}}^H\mathbf{R}_{\mathbf{CL}}^{-1/2}\right)^{-1} = \mathbf{R}_{\mathbf{CL}}^{1/2}\hat{\mathbf{R}}_{\mathbf{x}}^{-1}\mathbf{R}_{\mathbf{CL}}^{1/2}$$

$$y = \mathbf{v}^H\hat{\mathbf{R}}_{\mathbf{x}}^{-1}\mathbf{x}$$

i.e., same solution unless training size changes

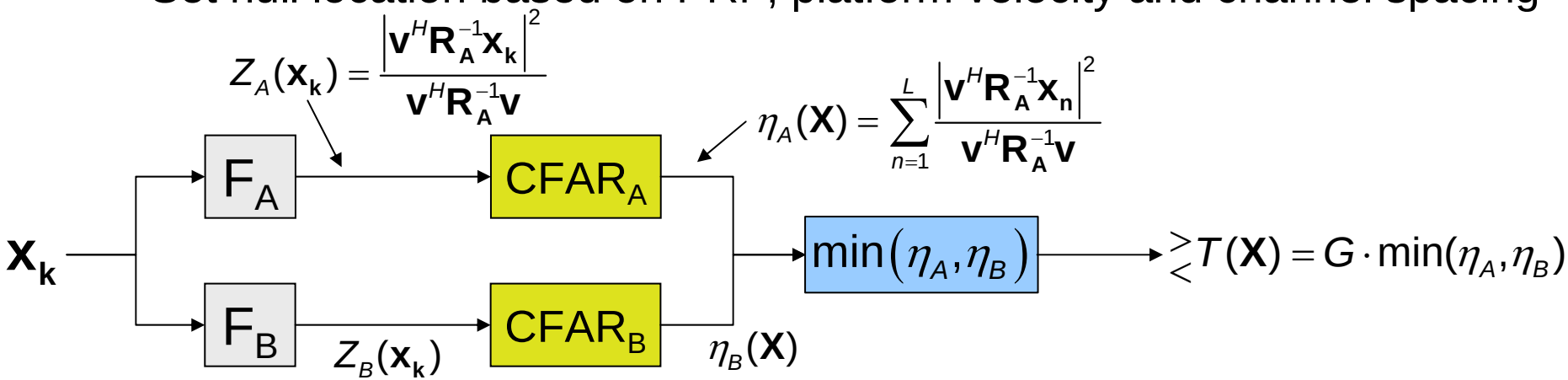
$$rank_{eff}\left(E\left[\hat{\mathbf{R}}_{\tilde{\mathbf{x}}}\right]\right) \le rank_{eff}\left(E\left[\hat{\mathbf{R}}_{\mathbf{x}}\right]\right) \Rightarrow \text{ Localized Training!}$$

- Localized training as a solution to clutter heterogeneity
  - Captures variations in distributed clutter
  - May exhibit sensitivity to TSD and clutter discretes

Note: in [2], data are rescaled by eigenvalues capturing multi-CPI clutter RCS estimate, dominant subspaces retained from influence of $\hat{\mathbf{R}}_{\mathbf{x}}$ (to correct errors)

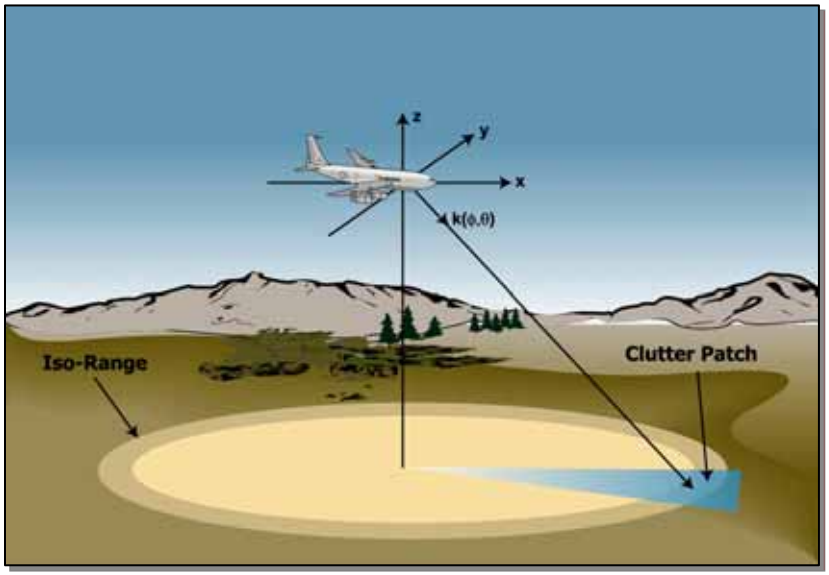
Nonlinear STAP Processing

- Proposed by Farina, Lombardo and Pirri [4-5] to…
  - Reduce computational burden, enhance performance in heterogeneous clutter environments
- Approach involves taking minimum of outputs of several linear filters with pre-selected weights and variable spectral width (presumption: clutter ridge location well known)
  - Set null location based on PRF, platform velocity and channel spacing



4. A. Farina, P. Lombardo and M. Pirri, "Nonlinear nonadaptive space-time processing for airborne early warning radar," *IEE Proceedings- Radar, Sonar Navigation*, Vol. 145, No. 1, February 1998, pp. 9-18.
5. A. Farina, P. Lombardo and M. Pirri, "Nonlinear STAP processing," *IEE Elect. & Comm. Eng. Journal*, February 1999, pp. 41-48.

Clutter Model



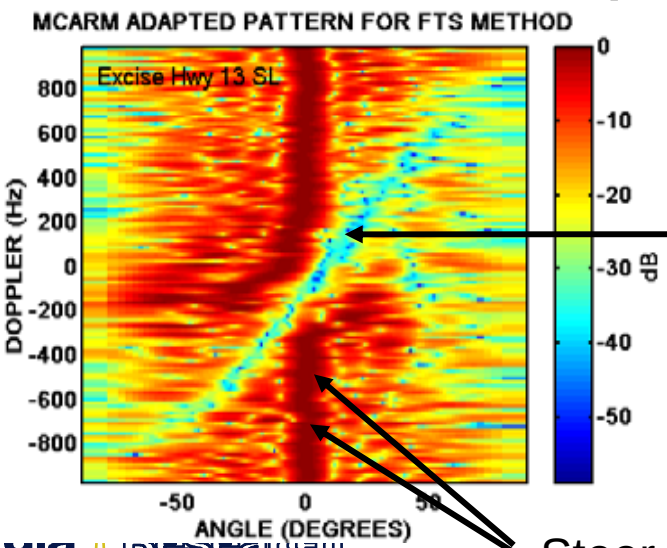
$$\mathbf{c_k} = \sum_{n=1}^{N_c} \alpha_n \mathbf{s_{s\text{-}t}}(f_{s/n}, f_{d/n})$$

$$f_{d/n} = \frac{2}{\lambda} \mathbf{k_p}(\phi_n, \theta_n) \cdot \mathbf{v_p}$$

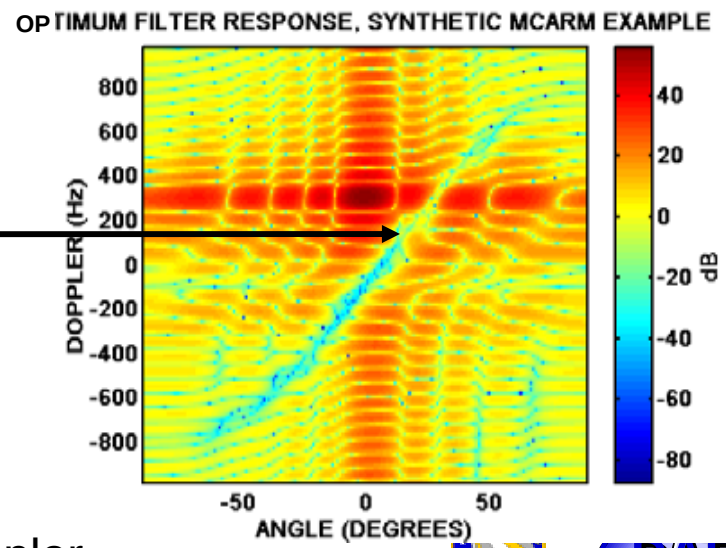
$$f_{s/n} = \frac{1}{\lambda} \mathbf{k_a} \cdot \mathbf{d_m}$$

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

Measured MCARM Example



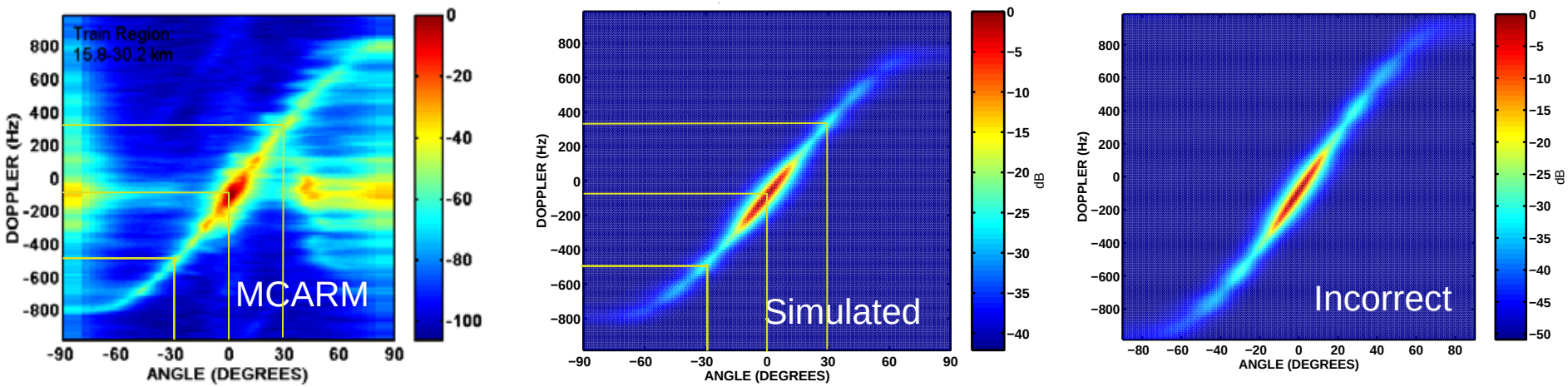
Simulated

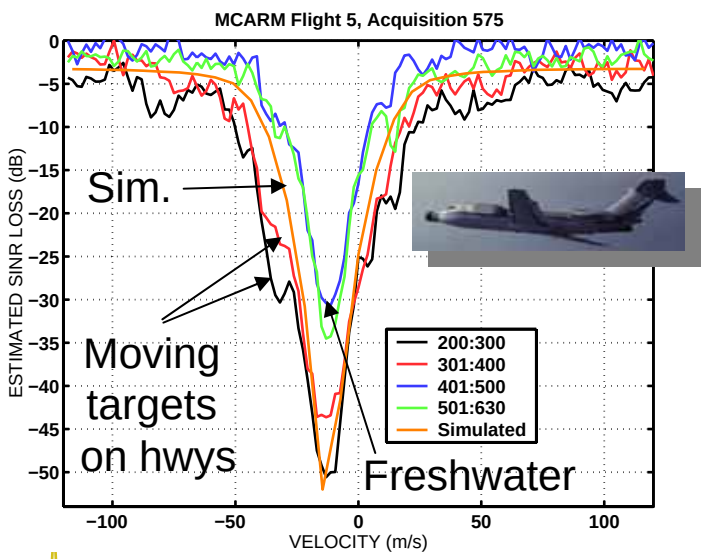


Steer to all Doppler

Comparison With Measured Data

Errors in knowledge or model are critical





Requirements:

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

Step 1: Estimate 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

Simple 2-DoF Results:

Phase Error	Null Depth
10°	15 dB
2°	29 dB
1°	35 dB
0.1°	55 dB

Magnitude Error (Relative to 1.0)	Null Depth
0.2	14 dB
0.1	20 dB
0.05	26 dB
0.025	32 dB

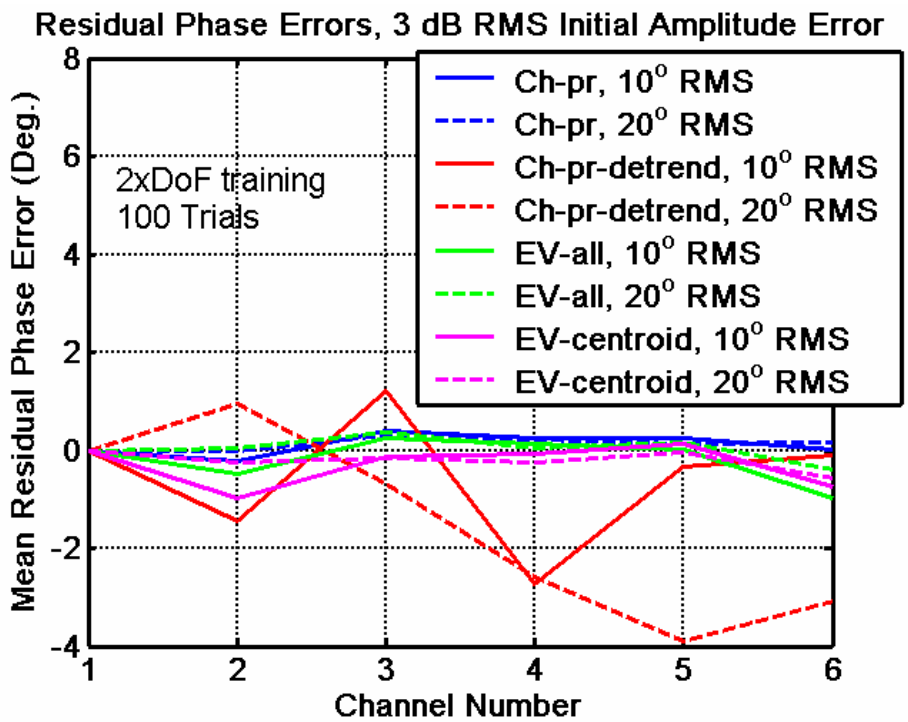
KASSPER array calibration goal & consequent requirements:

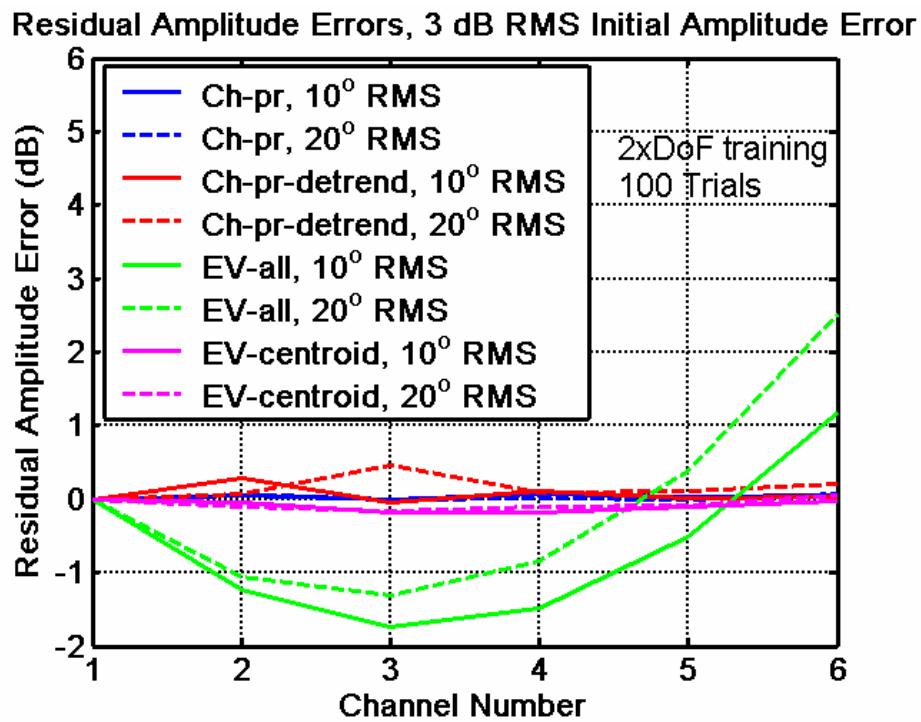
<u>30 dB Cancellation</u>

- < 2° phase error
- < 0.025 (0.1 dB) magnitude error

Calibration Performance

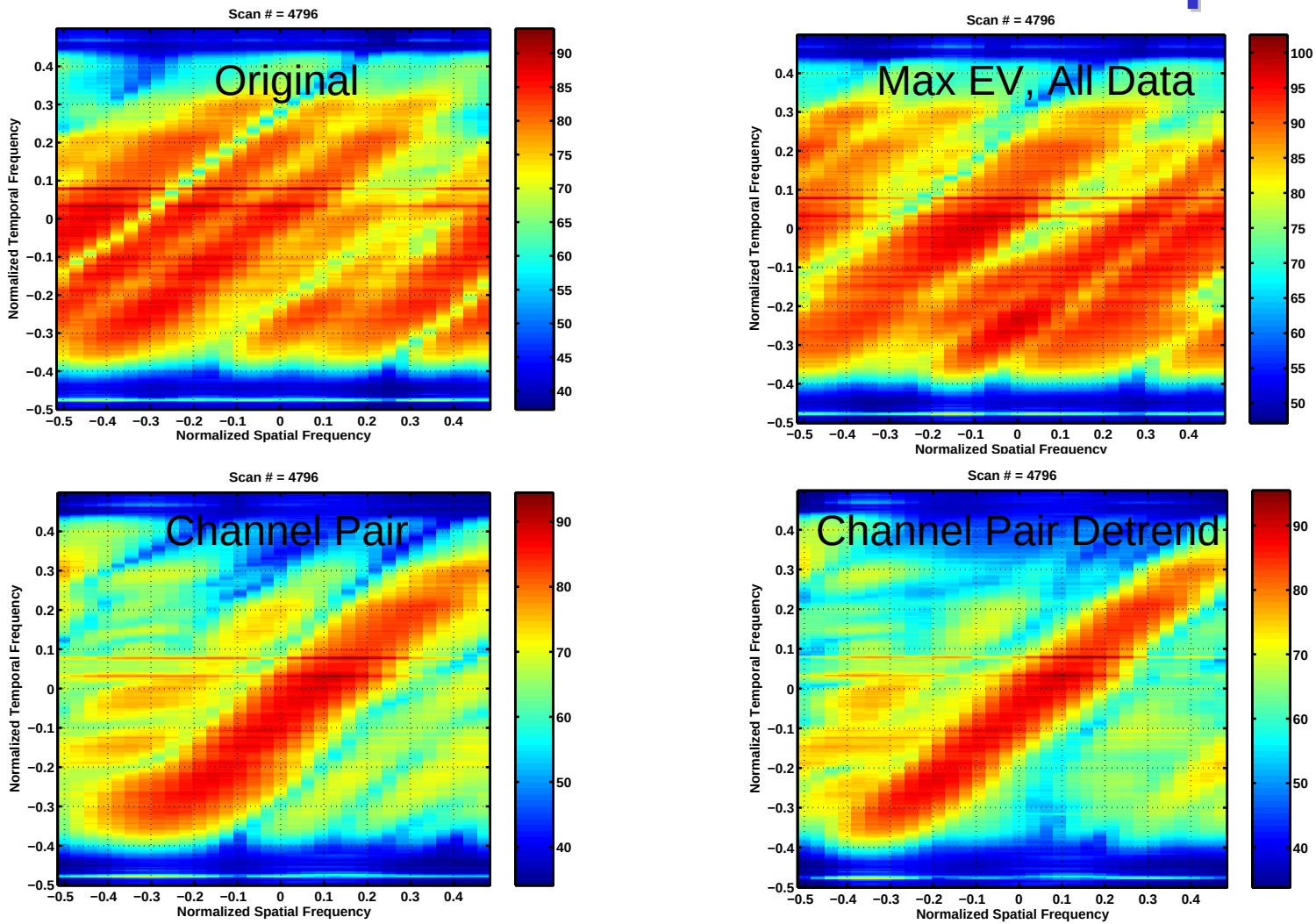
- Calibration is critical to effective KAPE operation
  - Eigenvectors of modeled covariance should maximally project onto actual interference subspace
- Cal effectiveness assessed by comparing estimated SINR loss null depth to maximum eigenvalue of traditional covariance estimate





* Synthetic X-band, 6 channel, 32 pulse example used in previous analysis

Calibration: FOPEN Data Example



* FOPEN data is property of Northrop Grumman Corp.
Data provided courtesy of Dr. Marshall Greenspan.

Georgia Tech Research Institute

NORTHROP GRUMMAN Electronic Systems

DARPA

Step 2: Estimate Clutter Amplitude

Least Squares Estimator

$$\mathbf{x_k} \approx \sum_{\substack{\text{lower}\\ \text{angle}\\ \text{limit}}}^{\substack{\text{upper}\\ \text{angle}\\ \text{limit}}} \alpha_{\text{n/k}} \mathbf{v_{s\text{-}t}}(\phi_{n/k}, \theta_{n/k}) = \mathbf{Va}$$

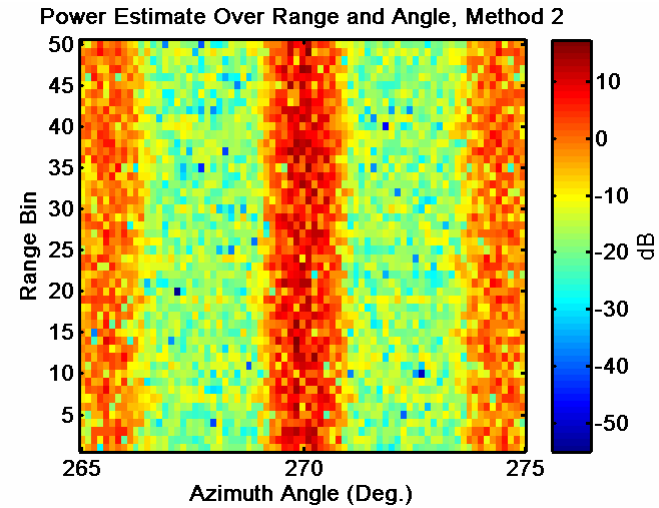
$$\mathbf{a} = \left(\alpha_{\text{n/k}}\right)_{n=1}^{N_c}; \quad \mathbf{V} = \left[\mathbf{v_{s\text{-}t}}(1) \quad \mathbf{v_{s\text{-}t}}(2) \quad \cdots \quad \mathbf{v_{s\text{-}t}}(N_c)\right]$$

$$\text{minimize LSE} \Rightarrow \min_{\mathbf{a}} \left\|\mathbf{x_k} - \mathbf{Va}\right\|_2^2$$

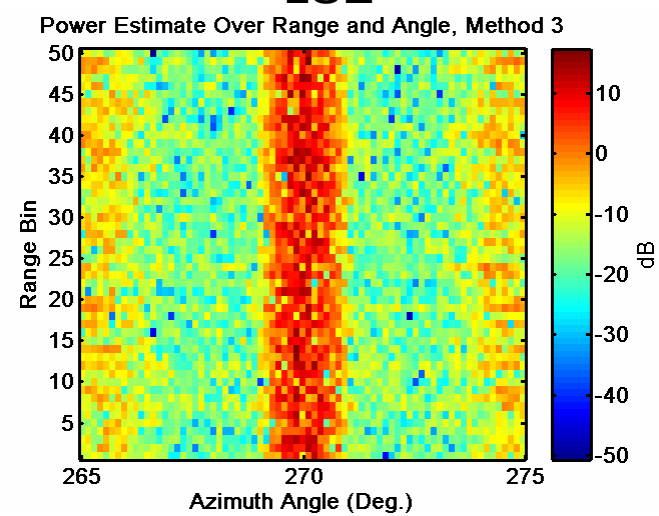
$$\mathbf{a} = \left(\mathbf{V}^H\mathbf{V}\right)^{-1}\mathbf{V}^H\mathbf{x_k}$$

- Several strategies
  - LS, space-time, single pulse, average over pulses
    - Issues: computational burden, space-time sampling, over/underdetermined LS solutions
  - Can use beampattern as weighting, but only in pseudo-homogeneous regions

S-T Estimator

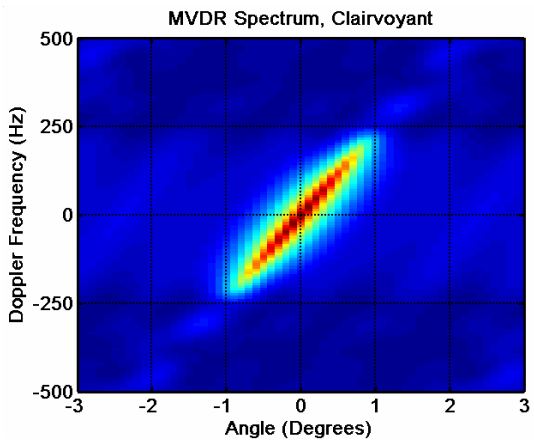


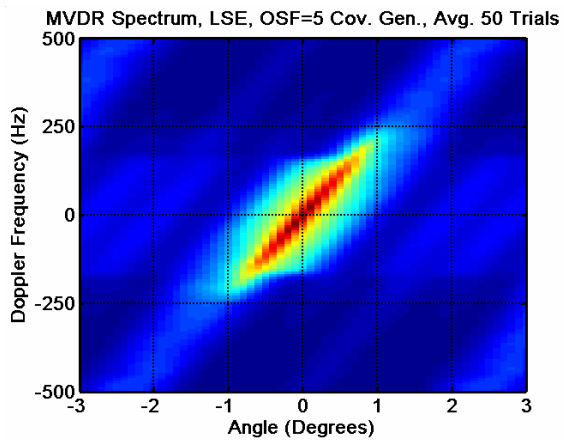
LSE

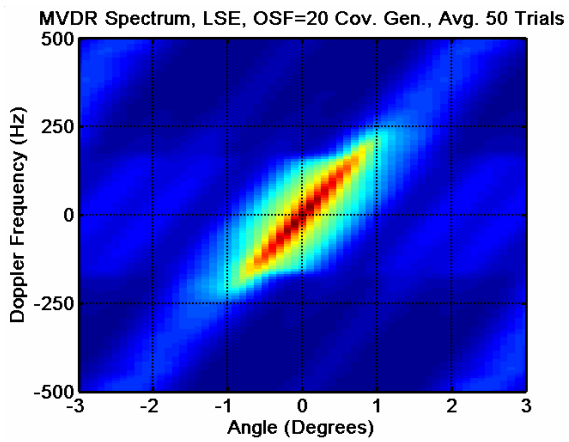


Sampling and Instantaneous Response

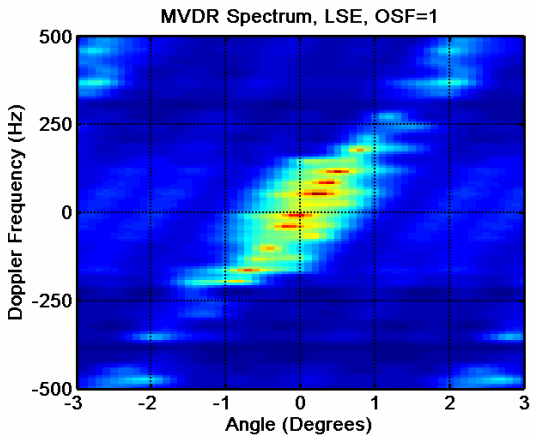
Mean

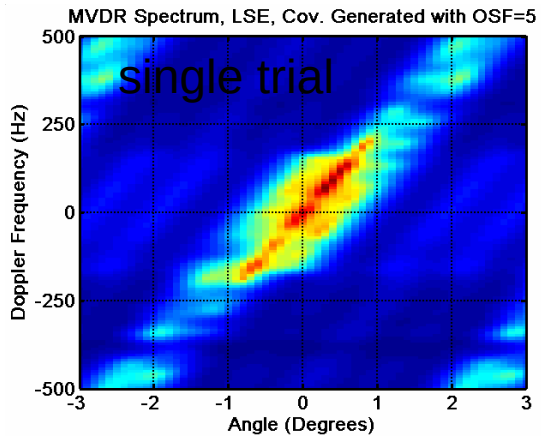


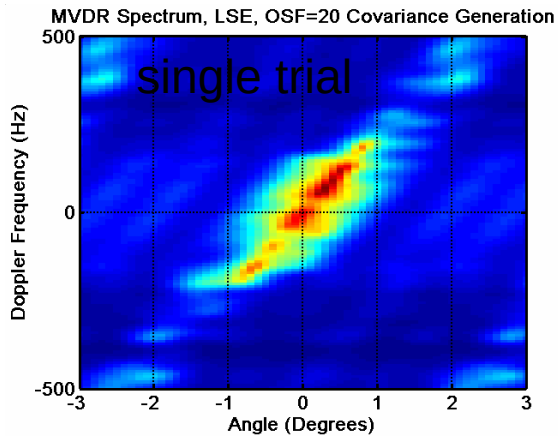




Average







* Spectra calculated with array error vector

Step 3: Form Candidate Whitening Filters

- Key factors: array normal, platform velocity, terrain height
- Errors in array normal
  - INU/GPS information provided on array normal direction
    - MCARM dataset provides array normal as header data, used for SAR fire-control, but especially matters when mechanically canting array
    - Shift in Doppler centroid, erroneous null locations when scanning
- Platform velocity generally known with sufficient accuracy
- DTED provides information on general terrain features
  - Excludes discretes, struggles to characterize discontinuous surfaces
  - Impact is slight in near-sidelooking case (no impact for uncrabbed SLAR case)
- Sensitivity analysis previously performed

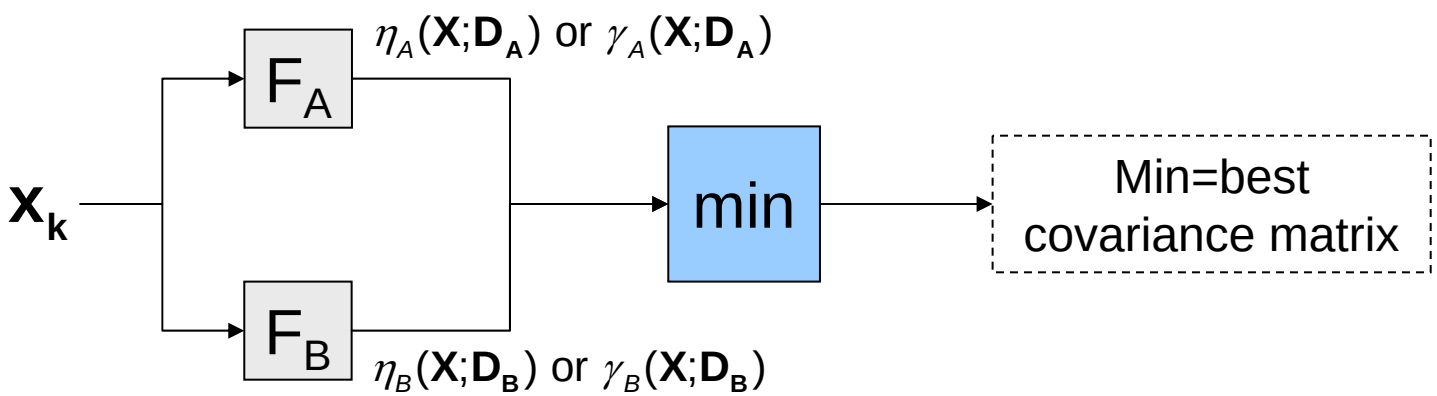
Step 4: Choose Best Filter Response

- **Presumption**: parametric covariance matrix adequately models clutter environment
- Over number of snapshots, calculate average degree of whitening or level of clutter cancellation
- Data normalization is a small concern
- Includes diagonal loading

$$\eta_A(\mathbf{X};\mathbf{D_A}) = \sum_{n=1}^{L} \frac{\left|\mathbf{v}^H \left(\mathbf{d_n}\mathbf{d_n}^H \square \mathbf{R_{c/n}}\right)^{-1} \mathbf{x_n}\right|^2}{\mathbf{v}^H \left(\mathbf{d_n}\mathbf{d_n}^H \square \mathbf{R_{c/n}}\right)^{-1} \mathbf{v}}$$

or

$$\gamma_A(\mathbf{X};\mathbf{D_A}) = \sum_{n=1}^{L} \mathbf{x_n}^H \left(\mathbf{d_n}\mathbf{d_n}^H \square \mathbf{R_{c/n}}\right)^{-1} \mathbf{x_n}$$



* Can refine over multiple angles

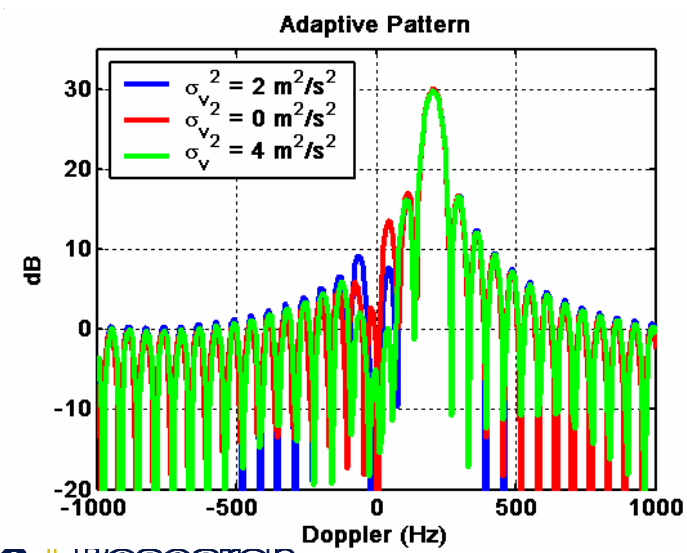
Step 5: Estimate Spectral Spread

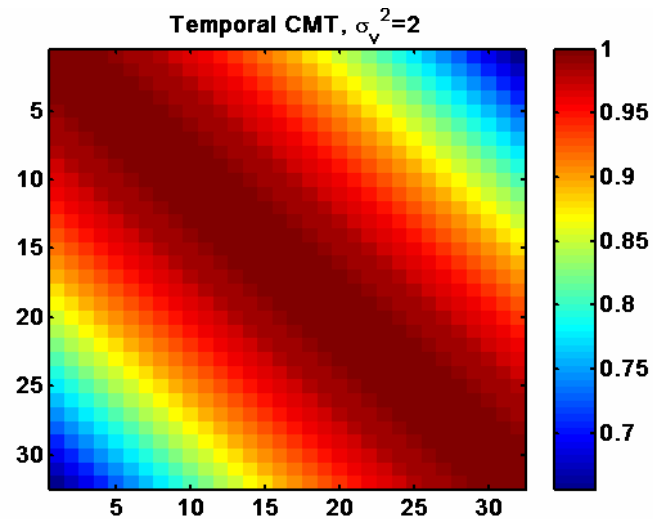
- Temporal decorrelation
  - Gaussian over water
  - Exponential (Billingsley) over terrain

$$\mathbf{R}'_{c/k} = \overbrace{\left(\mathbf{C}_{cmt_t} \otimes \mathbf{C}_{cmt_s}\right)}^{\mathbf{C}} \odot \mathbf{R}_{c/k}$$

- For modest bandwidth, spatial decorrelation is negligible
- Caveat: applying CMT to large discretes adversely affects MDV (remove large discretes in front-end)

$$\eta_{A'}(\mathbf{X};\mathbf{D}_{best};\mathbf{C}_A) = \sum_{n=1}^{L} \frac{\left|\mathbf{v}^H \left(\mathbf{C}_A\mathbf{C}_A^H \odot \mathbf{d}_n\mathbf{d}_n^H \odot \mathbf{R}_{c/n}\right)^{-1} \mathbf{x}_n\right|^2}{\mathbf{v}^H \left(\mathbf{C}_A\mathbf{C}_A^H \odot \mathbf{d}_n\mathbf{d}_n^H \odot \mathbf{R}_{c/n}\right)^{-1} \mathbf{v}}$$





Step 6: Applying Pre-Filter

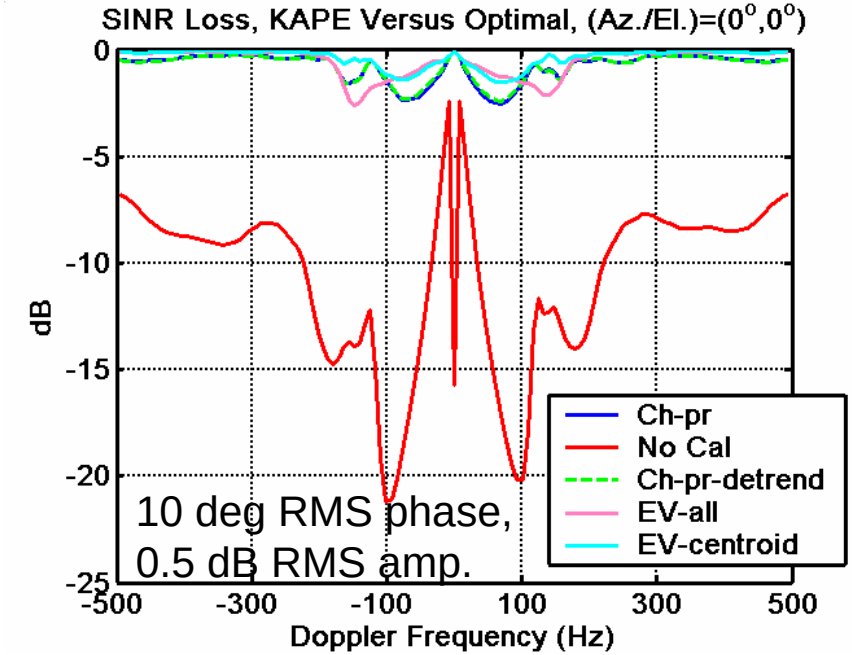
$$\mathbf{R}_{\mathbf{KAPE/k}} = \underbrace{\mathbf{C}_{best/k}\mathbf{C}_{best/k}^{H}}_{\text{spectral width}} \square \underbrace{\mathbf{d}_{best/k}\mathbf{d}_{best/k}^{H}}_{\text{null location}} \square \mathbf{R}_{\mathbf{c/n}} + \sigma_{DL}^{2}\mathbf{I}$$

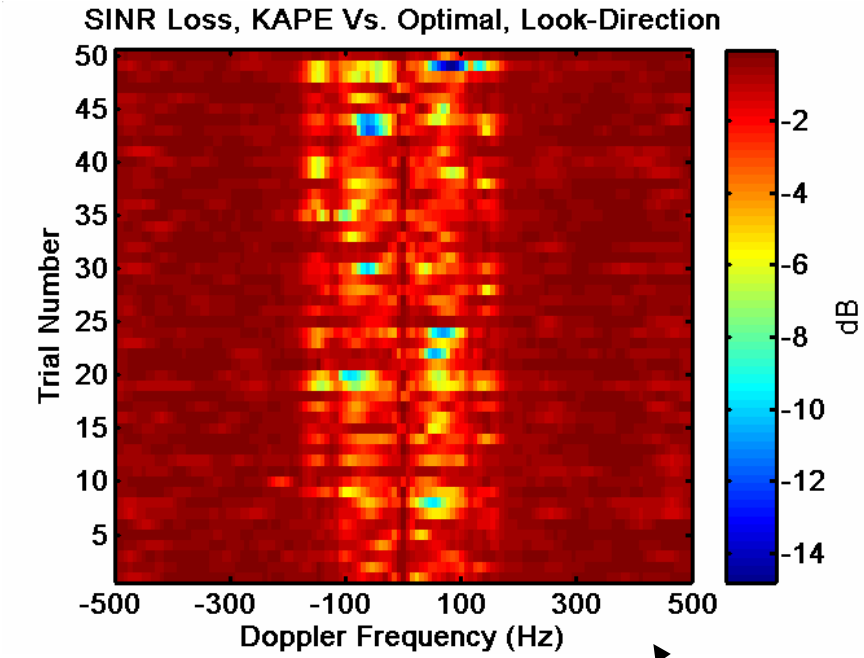
clutter amplitude

$$\tilde{\mathbf{x}}_{\mathbf{k}} = \mathbf{R}_{\mathbf{KAPE/k}}^{-1/2}\mathbf{x}_{\mathbf{k}}; \quad \tilde{\mathbf{v}}_{\mathbf{k}} = \mathbf{R}_{\mathbf{KAPE/k}}^{-1/2}\mathbf{v}_{\mathbf{k}}$$

- Store and retain range-varying covariance matrix
  - Or retain an averaged version
  - Memory requirements
- Provides information to assist in training stage
  - Interpolate missing information if necessary
- Gram-Schmidt for fast decomposition

Performance Potential

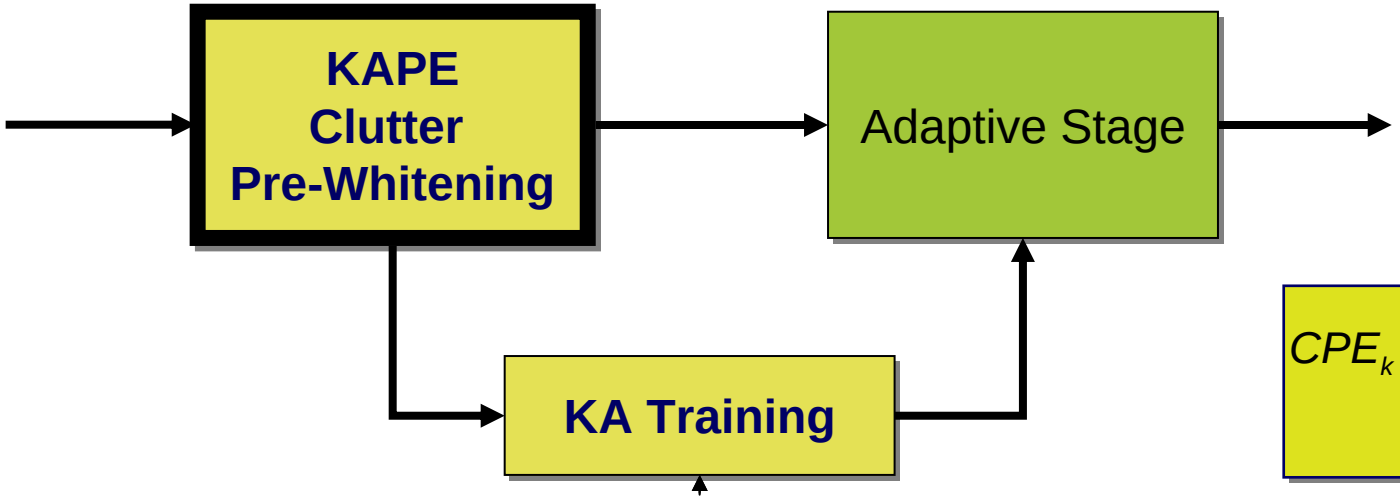




- Averaged power estimates on left, instantaneous on right
  - Same result for averaged covariance matrices
- Apply diagonal loading to modeled clutter covariance matrix
- Estimate accomplished with single range cell
- KAPE can provide *improved instantaneous performance*
  - Seen via detection analysis
- Synthetic X-band, 6 channel, 32 pulse example used in previous analysis

Why Include An Adaptive Step?

- Employ adaptive stage + KA training to…
  - Remove any model mismatch
  - Enable KA processing only in “troublesome” regions
  - Provide flexibility in merging KA and traditional adaptive processing
  - Noise jammer cancellation handled with front-end processor
- Variant of KAPE can provide training kernels



$$CPE_k = \frac{\tilde{\mathbf{x}}_k^H \mathbf{R}_{\mathbf{KA/k}} \tilde{\mathbf{x}}_k}{\frac{1}{K}\sum_k^K \tilde{\mathbf{x}}_k^H \mathbf{R}_{\mathbf{KA/k}} \tilde{\mathbf{x}}_k}$$

$$GIP_k = \frac{\tilde{\mathbf{x}}_k^H \mathbf{R}_{\mathbf{KA/k}}^{-1} \tilde{\mathbf{x}}_k}{\frac{1}{K}\sum_k^K \tilde{\mathbf{x}}_k^H \mathbf{R}_{\mathbf{KA/k}}^{-1} \tilde{\mathbf{x}}_k}$$

Summary

- Minimizing covariance estimation errors is focus of KAPE
  - Direct application of knowledge
  - Avoid anomalous response
- KAPE turns matrix estimation into estimation of model parameters
- Generally, given ownship navigation data, clutter ridge adequately known
  - Amplitude, spectral spread, array manifold
- Avoids TSD, potential for better instantaneous performance, can be used for screening outliers