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Knowledge-Aided Discrete Removal Techniques

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

Georgia Tech Research Institute (GTRI)
greg.showman@gtri.gatech.edu, 770.528.7719

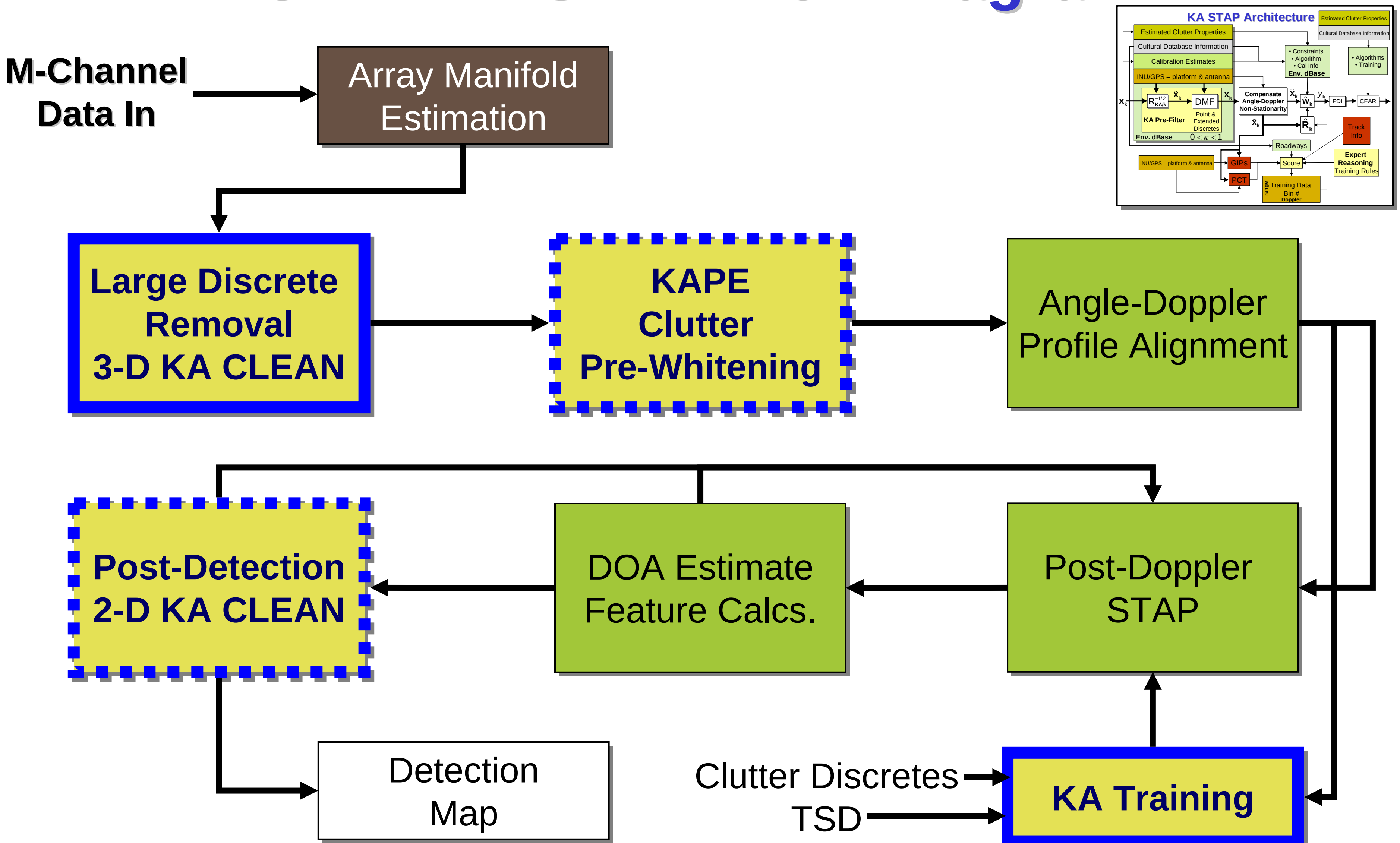
Outline

- Introduction
  - Discussion of Discrete Effects
  - Notional KASSPER Architecture
- Processing Solutions
  - Nulling (CLEAN)
  - Power Comparable Training (PCT)
- Processing Results
- Conclusions

Discrete Effects

- Heterogeneity challenges
  1. Targets in the secondary data (TSD)
  2. **Discrete returns**
  3. Amplitude & spectral variations; angle-Doppler non-stationarity, etc.
- Discretes in the training data not so serious
  - Contribution of any one discrete is averaged down
    - (Unless training is highly localized!)
    - Results in mild over-nulling of targets and clutter
  - Discretes are rigid; no CNR-induced ICM issues (“iceberg effect”)
- Primary concern is discretes in the CUT
  - Discrete itself is under-nulled $\Rightarrow$ false alarm
  - Also generates range-Doppler sidelobes $\Rightarrow$ multiple false alarms
    - Adaptive nulls are twice as deep as necessary, so…
    - The discrete problem worsens when distributed clutter power is low and discretes are strong $\Rightarrow$ <u>fine resolutions</u>

GTRI KA-STAP Flow Diagram



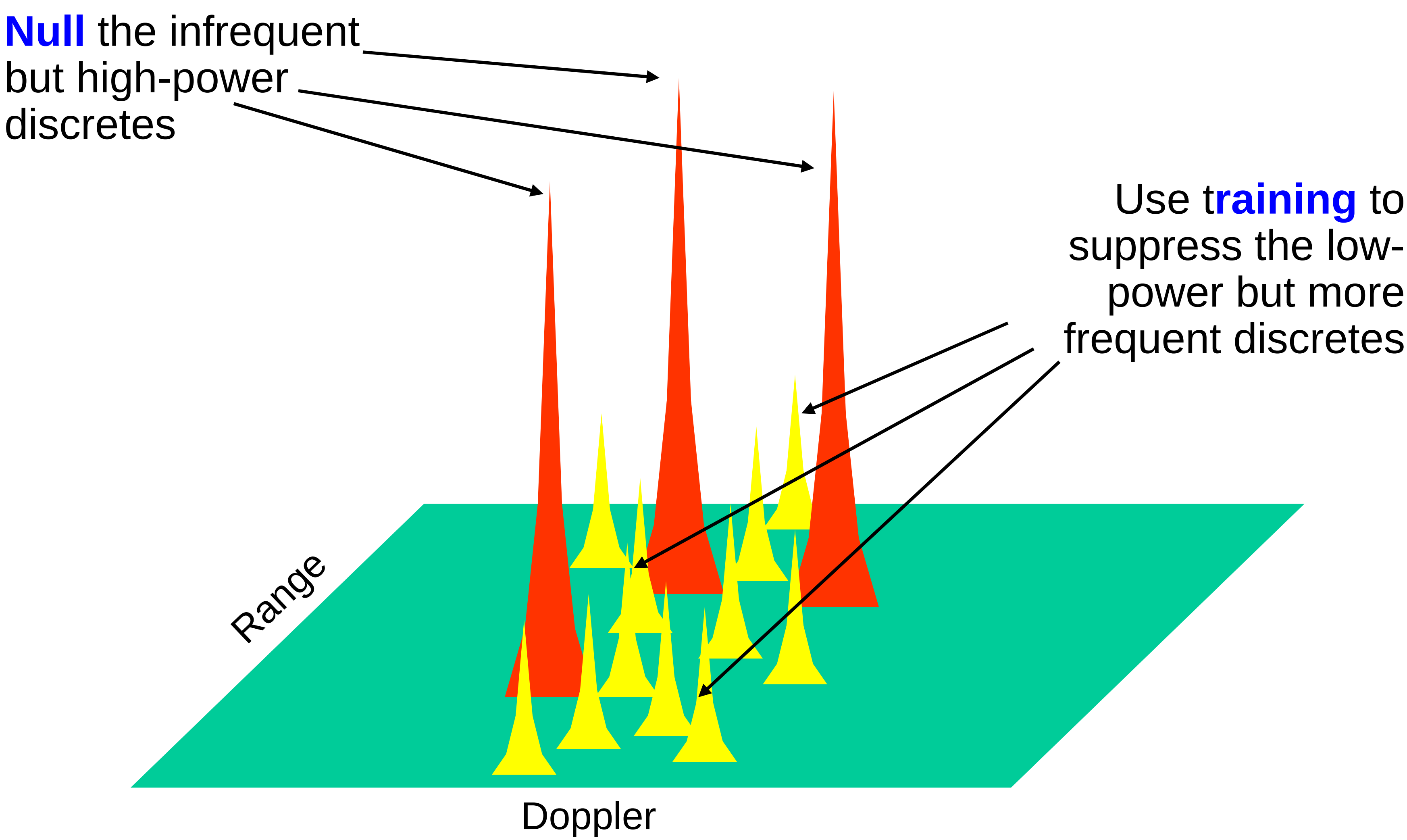
Discrete Mitigation Processing Flow

Raw Data CLEAN → KAPE → Post-Doppler → PCT → EFA → AMF CLEAN

- Raw Data CLEAN
  - Orthogonal projection in range-Doppler-angle
  - Remove strong discretes prior to adaptive processing
- KAPE
  - Scale pre-whitening filter with estimated clutter power
  - Suppress discretes (strong and weak?)
- PCT (Power Comparable Training)
  - Bins with strong returns tiled together for training
  - Suppress weaker (but more numerous) discretes
- AMF CLEAN
  - Orthogonal projection based on AMF output
  - Remove detections due to discretes

All 4 methods are included for development and evaluation. Will down-select for final architecture.

Discrete Mitigation Approach



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CLEAN Algorithm

Find return with maximum power, e.g.,

$$Power = \frac{\left|\mathbf{v}^H \mathbf{x}_k\right|^2}{\mathbf{v}^H \mathbf{v}}, \ \mathbf{v} = \mathbf{v}(angle, Doppler)$$

$$\hat{\mathbf{v}}_{kMax} = \arg \max_{\mathbf{v}, k} \frac{\left|\mathbf{v}^H \mathbf{x}_k\right|^2}{\mathbf{v}^H \mathbf{v}}$$

$$\hat{\alpha}_k = \frac{\hat{\mathbf{v}}_{kMax}^H}{\hat{\mathbf{v}}_{kMax}^H \hat{\mathbf{v}}_{kMax}} \mathbf{x}_k$$

$$\hat{\mathbf{s}}_{kMax} = \hat{\alpha}_k \hat{\mathbf{v}}_{kMax}$$

$$\mathbf{x}_k = \mathbf{x}_k - \mu \hat{\mathbf{s}}_{kMax}, \ 0 \le \mu \le 1$$

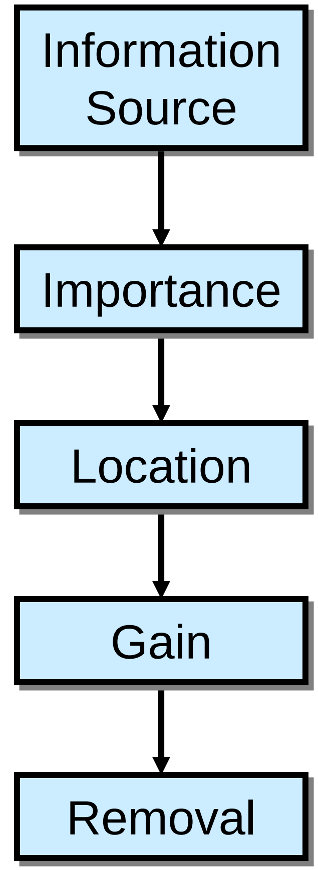
Traditional and MLE CLEAN

	Finding the Peak	Determining Signal Complex Gain
Raw Data Domain	$\hat{\mathbf{v}}_k = \arg\max_{\mathbf{v},k} \frac{\left\|\mathbf{v}^H \mathbf{x}_k\right\|^2}{\mathbf{v}^H \mathbf{v}}$	$\hat{\alpha}_k = \frac{\hat{\mathbf{v}}_k^H \mathbf{x}_k}{\hat{\mathbf{v}}_k^H \hat{\mathbf{v}}_k}$
Whitened Domain	$\hat{\mathbf{v}}_{kMLE} = \arg\max_{\mathbf{v},k} \frac{\left\|\mathbf{v}^H \mathbf{R}^{-1} \mathbf{x}_k\right\|^2}{\mathbf{v}^H \mathbf{R}^{-1} \mathbf{v}}$	$\hat{\alpha}_{kMLE} = \frac{\hat{\mathbf{v}}_{kMLE}^H \mathbf{R}^{-1} \mathbf{x}_k}{\hat{\mathbf{v}}_{kMLE}^H \mathbf{R}^{-1} \hat{\mathbf{v}}_{kMLE}}$

- Advantages of <u>raw data</u> CLEAN
  - Easy to implement, operates in range-Doppler-angle space
  - Does not require knowledge of $\mathbf{R}$
- Advantages of <u>maximum-likelihood estimated</u> CLEAN
  - Superior parameter estimates (angle-Doppler-amplitude-phase)
  - However, complex gain estimator is very sensitive to quality of $\mathbf{R}$

General Nulling Procedure

- Information source
  – What measurements are used to ID discretes?
- Importance
  – Which discretes in the scene are most significant?
- Location
  – Where is the discrete in range-angle-Doppler?
- Gain
  – What is the amplitude and phase of the discrete?
- Removal
  – How do I mitigate discrete returns?



Estimating Gain, Removing Discrete (1 of 2)

- Orthogonal projection (nulling) matrix $\mathbf{T}$
  - STAP output statistics: $y = \mathbf{w}^H\mathbf{x}, \quad \mathbf{w} \propto \mathbf{R}^{-1}\mathbf{s}$
  - CLEAN: $y = \mathbf{w}^H(\mathbf{T}^H\mathbf{x})$
  - Other techniques: $y = (\mathbf{T}\mathbf{w})^H\mathbf{x}$
- All approaches null in a similar fashion:
  - CLEAN:

$$\boxed{\mathbf{T}_{CLEAN}^H = \mathbf{I} - \mu \mathbf{s}_{Discrete} \frac{\mathbf{s}_{Discrete}^H}{\mathbf{s}_{Discrete}^H \mathbf{s}_{Discrete}}}$$

  - Colored loading:

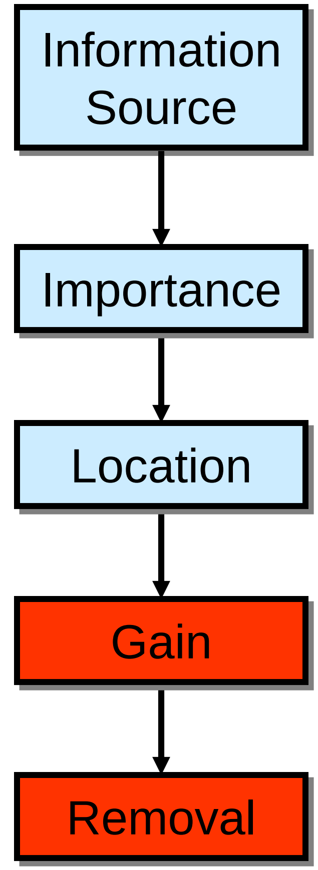
$$\mathbf{R} \to \mathbf{R} + \beta \mathbf{s}_{Discrete}\mathbf{s}_{Discrete}^H$$

$$\boxed{\mathbf{T}_{CL}^H = \mathbf{I} - \mathbf{s}_{Discrete} \frac{\mathbf{s}_{Discrete}^H \mathbf{R}^{-1}}{\frac{1}{\beta} + \mathbf{s}_{Discrete}^H \mathbf{R}^{-1} \mathbf{s}_{Discrete}}}$$

  - Constrained optimization:

$$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{R} \mathbf{w} \ \text{s.t.} \ \begin{array}{l} \mathbf{w}^H \mathbf{s} = 1 \\ \mathbf{w}^H \mathbf{s}_{Discrete} = 0 \end{array}$$

$$\boxed{\mathbf{T}_{Constrained}^H = \mathbf{I} - \mathbf{s}_{Discrete} \frac{\mathbf{s}_{Discrete}^H \mathbf{R}^{-1}}{\mathbf{s}_{Discrete}^H \mathbf{R}^{-1} \mathbf{s}_{Discrete}}}$$



Estimating Gain, Removing Discrete (2 of 2)

- All approaches effectively null the CUT data snapshot
- 1st difference
  - CLEAN nulls data before covariance matrix estimation
  - Hence, CLEAN removes discretes from training data
  - This can be good or bad, depending on the environment
- 2nd difference
  - CLEAN does not perform ML estimate of gain
  - However, nulls on discretes are always very deep, so all three methods perform about the same
  - In addition, MLE is poor if estimate of $\mathbf{R}$ is poor
    - E.g., an estimate of $\mathbf{R}$ from finite samples or with discretes

$$\mathbf{T}_{CLEAN}^{H} = \mathbf{I} - \mu \mathbf{s}_{Discrete} \frac{\mathbf{s}_{Discrete}^{H}}{\mathbf{s}_{Discrete}^{H}\mathbf{s}_{Discrete}}$$

$$\mathbf{T}_{CL}^{H} = \mathbf{I} - \mathbf{s}_{Discrete} \frac{\mathbf{s}_{Discrete}^{H}\mathbf{R}^{-1}}{\frac{1}{\beta} + \mathbf{s}_{Discrete}^{H}\mathbf{R}^{-1}\mathbf{s}_{Discrete}}$$

$$\mathbf{T}_{Constrained}^{H} = \mathbf{I} - \mathbf{s}_{Discrete} \frac{\mathbf{s}_{Discrete}^{H}\mathbf{R}^{-1}}{\mathbf{s}_{Discrete}^{H}\mathbf{R}^{-1}\mathbf{s}_{Discrete}}$$

ML Estimate

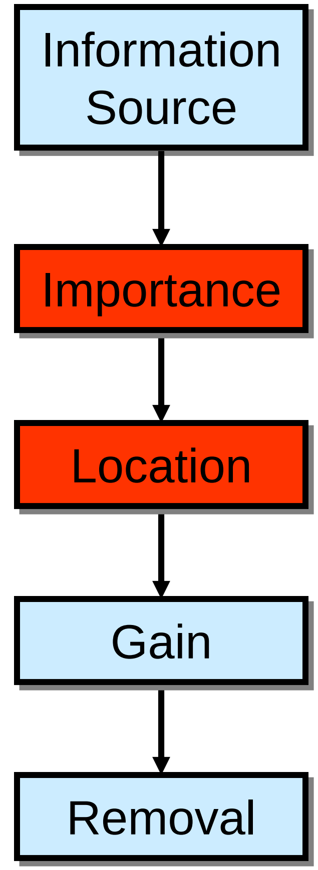
Nulling: Location and Importance

Raw Data Domain

$$\hat{\mathbf{v}}_k = \arg \max_{\mathbf{v},k} \frac{\left|\mathbf{v}^H \mathbf{x}_k\right|^2}{\mathbf{v}^H \mathbf{v}}$$

Whitened Domain (MLE)

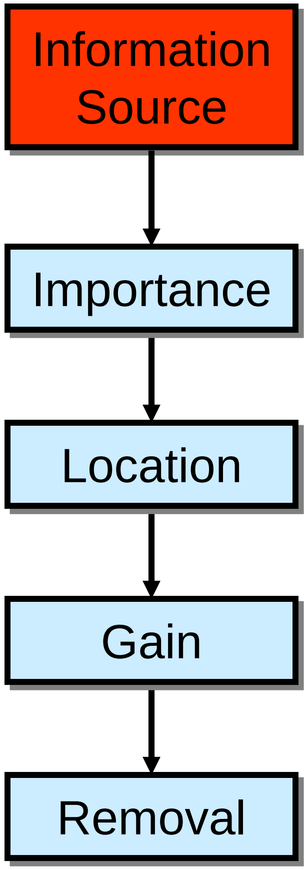
$$\hat{\mathbf{v}}_{kMLE} = \arg \max_{\mathbf{v},k} \frac{\left|\mathbf{v}^H \mathbf{R}^{-1} \mathbf{x}_k\right|^2}{\mathbf{v}^H \mathbf{R}^{-1} \mathbf{v}}$$



- Location
  - Most methods use the expression at left, find maximum in range-Doppler image
  - Little change in performance from applying MLE form
- Importance
  - Test candidate cells using 1-D (range-only) OS-CFAR
    - Operate on discretes only; ignore distributed clutter
  - Use MLE form to chose peak
    - MLE discretes tend to have greater impact at the detector (after EFA, etc.) by several dB
    - **KAPE can provide the requisite high-fidelity $\mathbf{R}$**

Information Sources for Discrete Nulling

- Radar-independent sources
  - Maps, photographs
  - Data bases
  - Useful for general cueing only
    - “Discretes may be present”
- Radar-generated sources
  - SAR imagery (previously collected)
  - Short-dwell data (GMTI CPI)
  - Long-dwell data
    - E.g., multi-channel SAR collections
    - CLEAN on long-dwell data yields a finer null as compared to nulling (CLEAN or CL or constraints) on short-dwell data sets

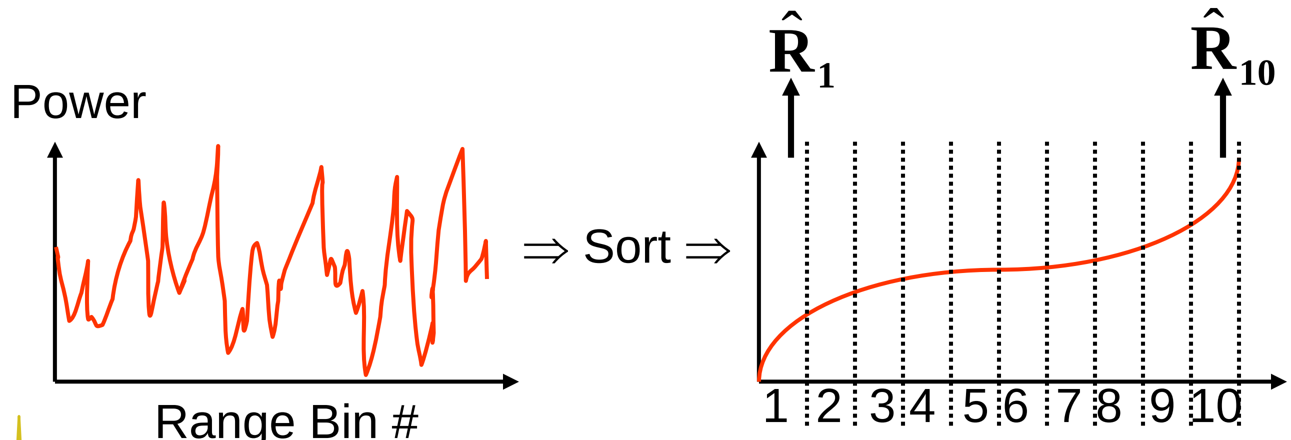


CLEAN Implementation Caveats

- Caveat #1: Processing Time
  - CLEAN introduces a latency in the processing chain
  - CLEAN does not lend itself well to parallel processing
- Caveat #2: Array Calibration
  - 2-D space-time nulling requires accurate array calibration
  - Alternatively, one can null in Doppler, and blank over all angle
- Caveat #3: Targets
  - Exo-clutter (and strong endo-clutter) targets can be CLEANed
  - CLEANed scatterers must be recorded and post-processed
- Caveat #4: Complex Man-Made Scatterers
  - Real discrete returns are not necessarily point-like
    - Broad-side flashes
    - Collections of multiple under-resolved scatterers
  - Can CLEAN iteratively remove such returns without introducing residual energy off the clutter ridge?

Power Comparable Training (PCT)

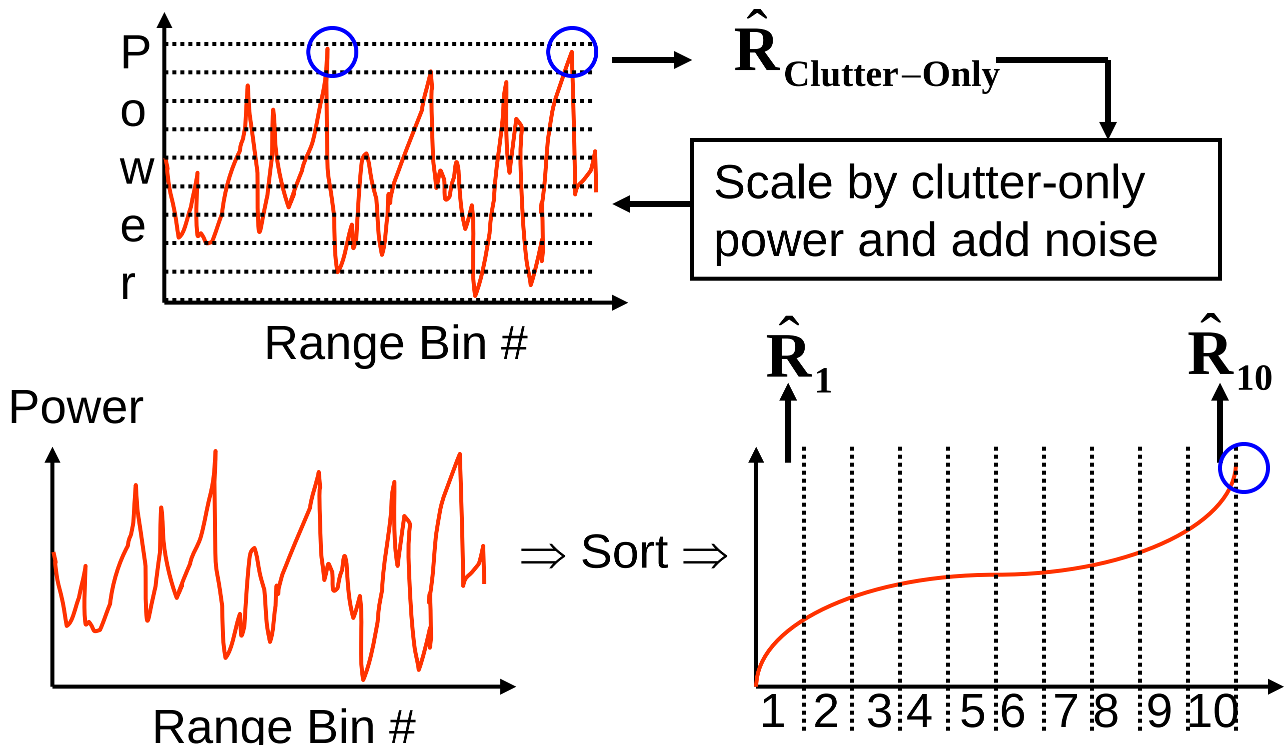
- Training implementation of Power Variable Training (PVT)
  - PVT generates one covariance matrix estimate
  - Then scales clutter subspace with power of current CUT
- PCT
  - Sort K range bins (e.g., 1,000) by power
  - Partition into L tiles (e.g., 10) by power
  - K/L samples per tile (e.g., 100), enough for full-rank covariance
  - Estimate covariance matrix and weight vector for each tile
  - Apply weight vector to all CUTs in the appropriate tile



PVT and PCT

- PCT a “poor man’s PVT”
  - PCT covariance matrix estimations are well-conditioned
  - PCT avoids decompositions and sub-space power measurements
  - PVT requires fewer range samples
  - PVT mitigates infrequent but strong discretes more aggressively

Both PVT (top) and PCT (bottom) require (1) clutter localization (e.g. post-Doppler implementation), (2) snapshots containing targets have been screened, (3) clutter possesses angle-Doppler stationarity.



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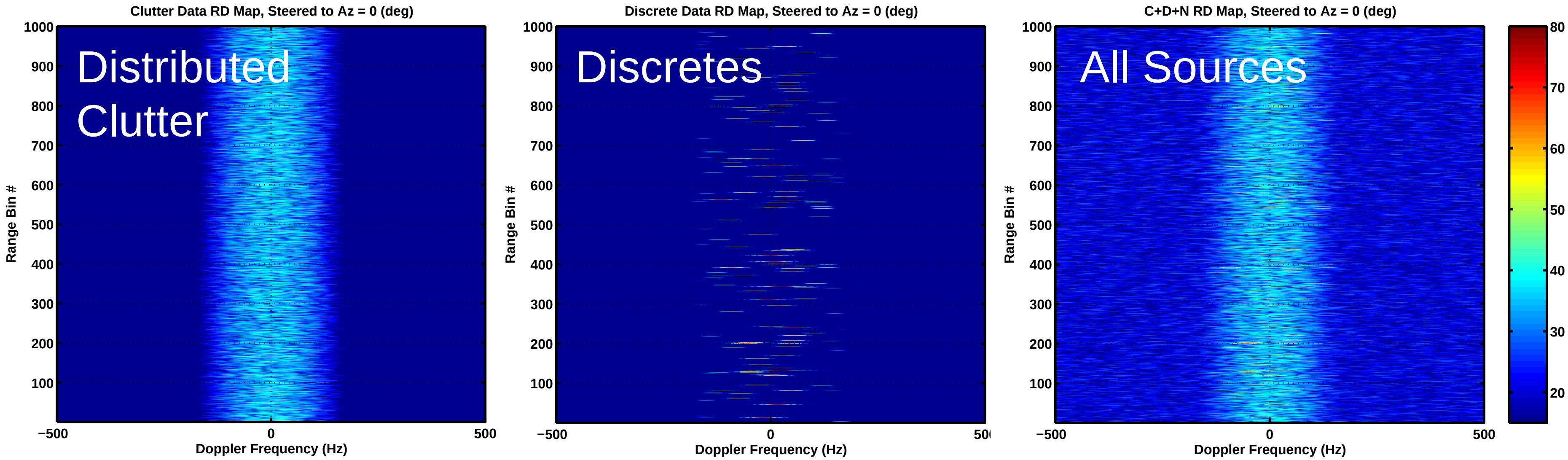
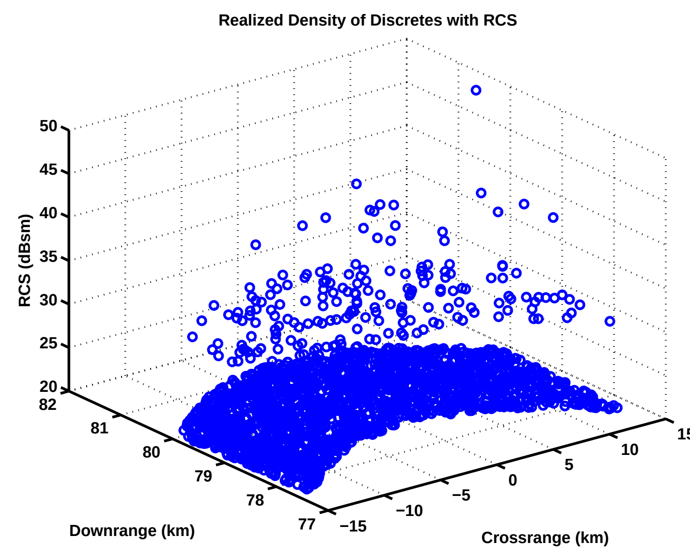
"Global Hawk"-Type Radar Example



- 6-channel X-band radar
  - 64 pulses, 60 MHz BW
  - 2.2-meter array
  - Side-looking, 80-km range
- Random discrete distribution
  - 30 20-dBsm discretes per km^2
  - Equi-power (3 x 30-dBsm/ km^2, etc.)



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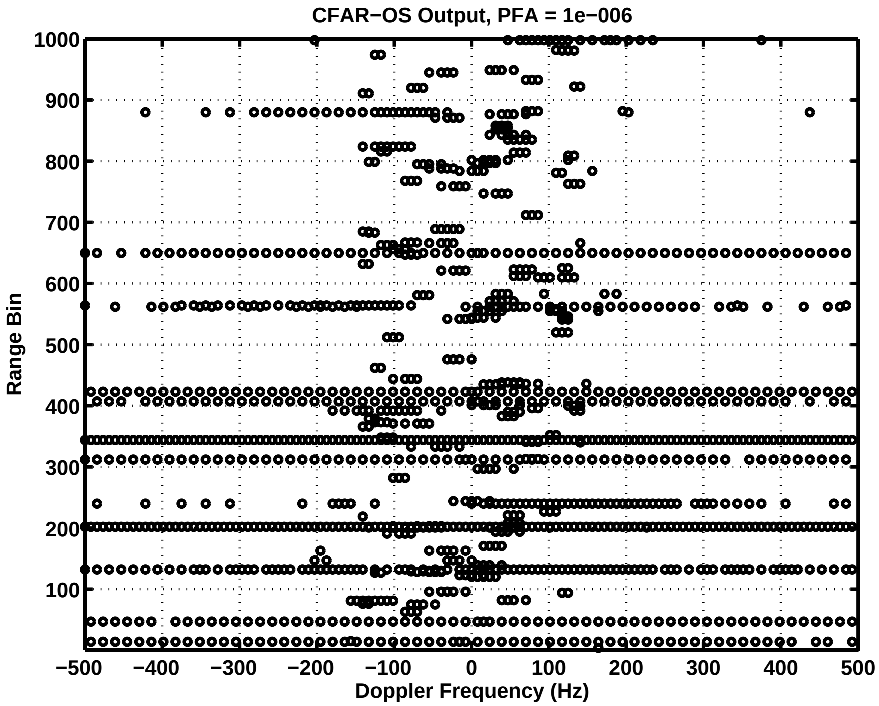
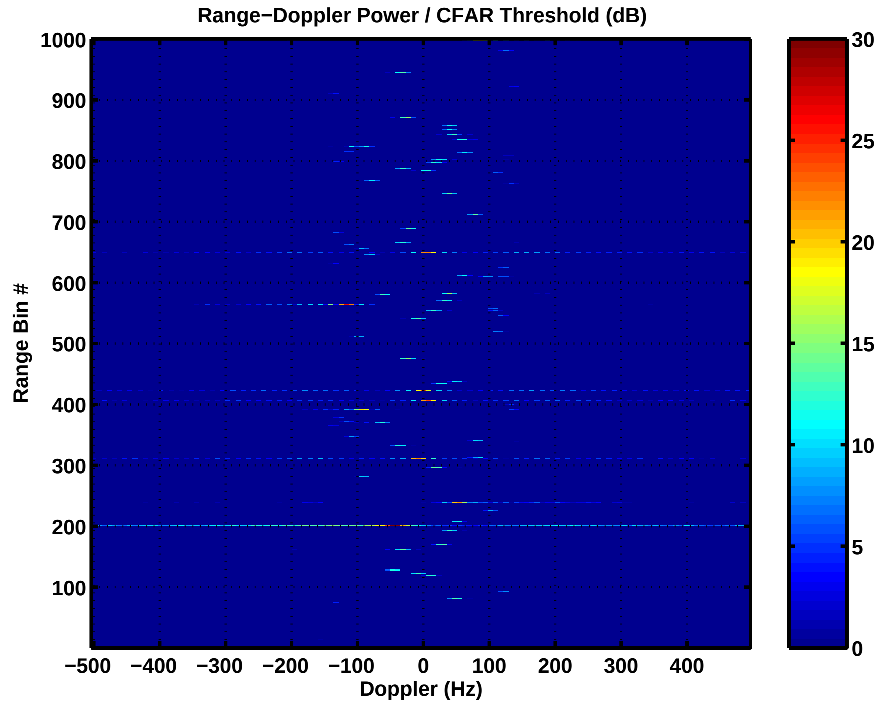
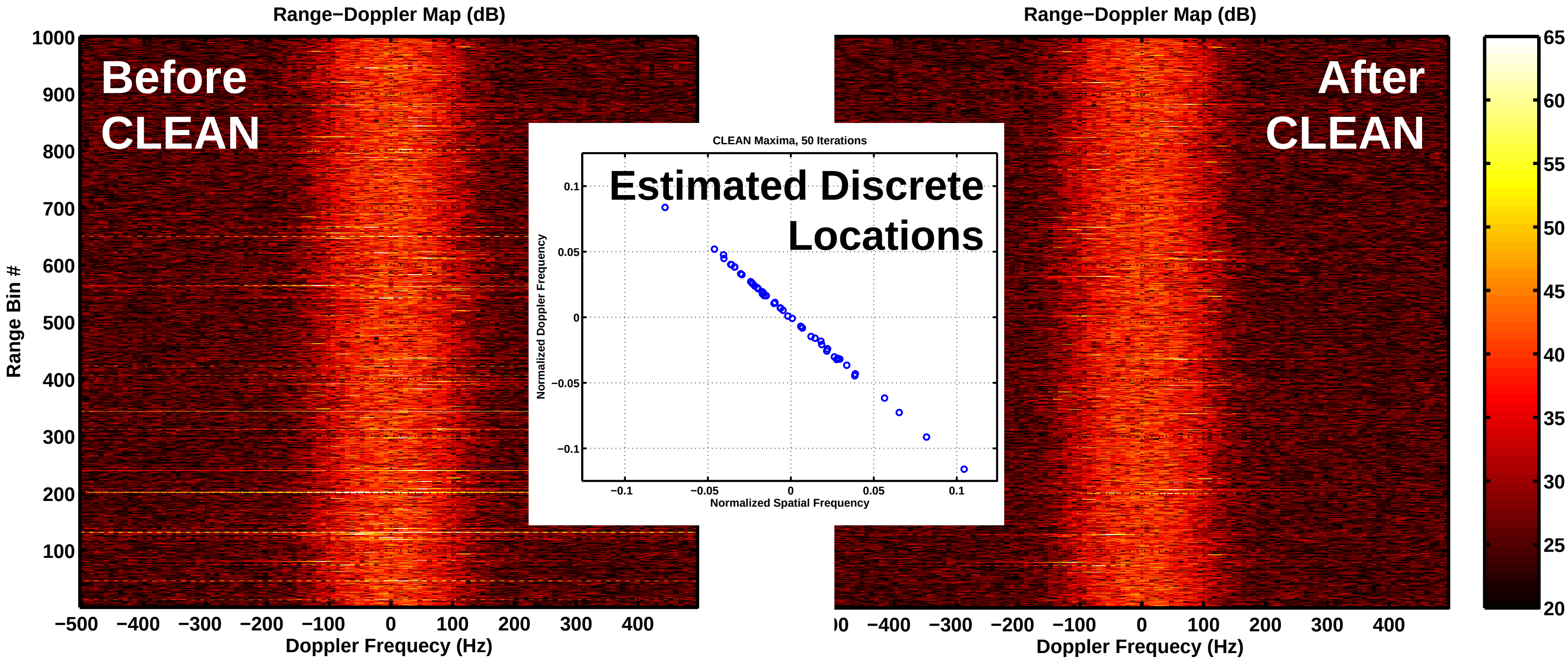
Ordered Statistic (OS) CFAR





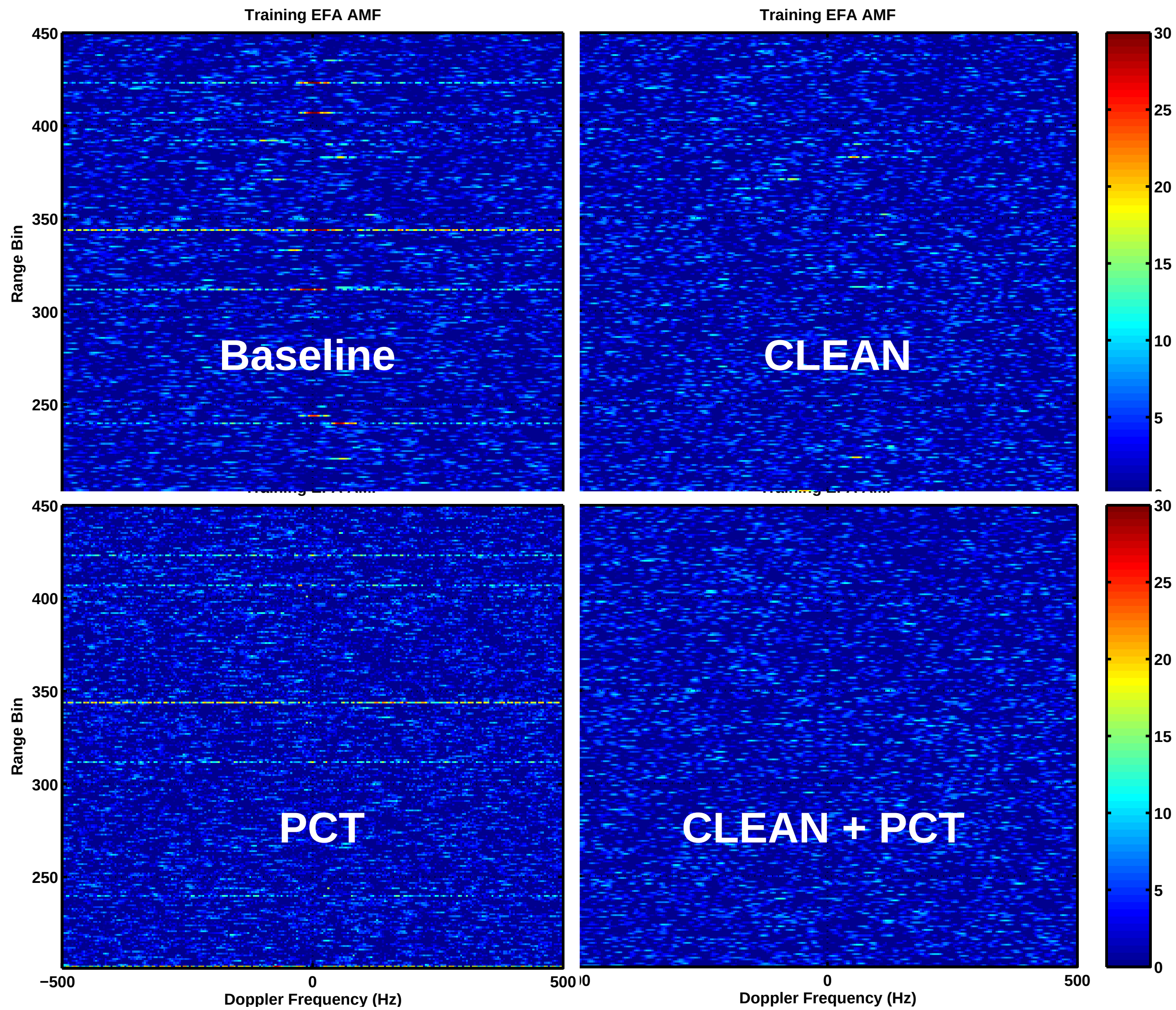
- OS-CFAR detections
  - Candidate return must exceed threshold to be declared a discrete
  - In this way, CLEAN avoids operating on distributed clutter
- R-D Map / CFAR threshold
  - Candidate returns examined relative to other returns
  - Provides stopping criterion for CLEAN

CLEAN Range-Doppler Maps



- CLEAN results
  - No clutter suppression (raw data)
  - 50 iterations (50 discretes removed)
  - Weaker discretes and distributed clutter remain
- Discrete locations
  - Clutter ridge is apparent
  - **IMU-derived array normal is required to differentiate slow movers from discretes in low clutter areas**

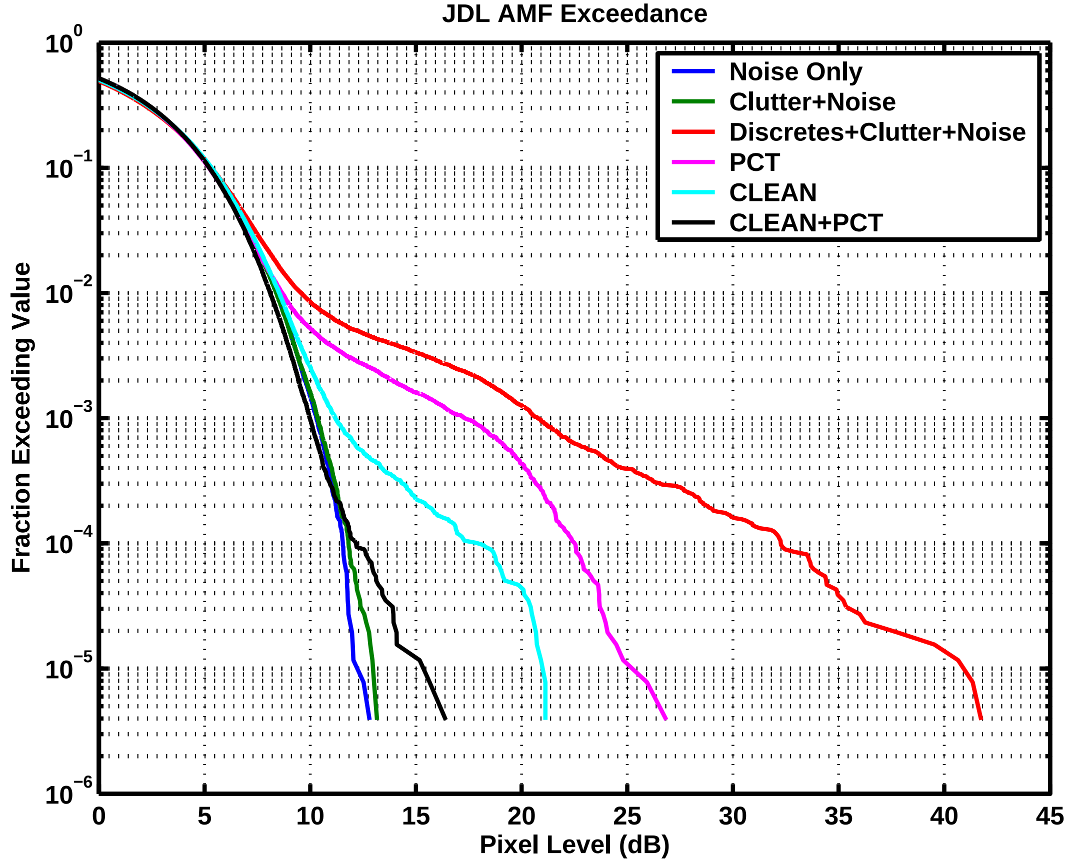
Example EFA AMF Images



The benefit of PCT and CLEAN w.r.t. to the baseline is a function of the discrete powers and densities, strength of distributed clutter, and clutter angle-Doppler properties.

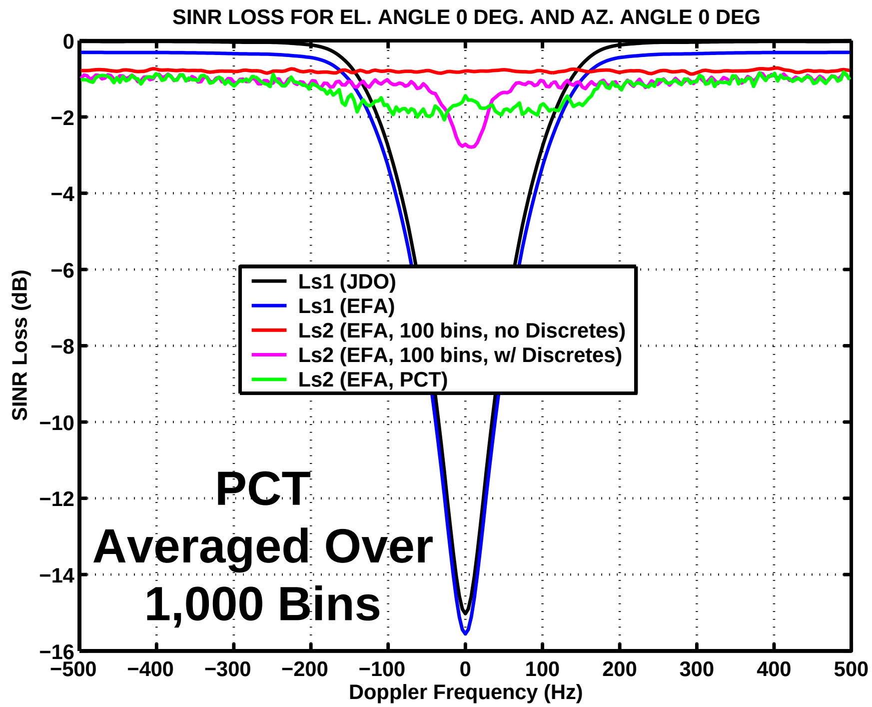
CLEAN & PCT Exceedances

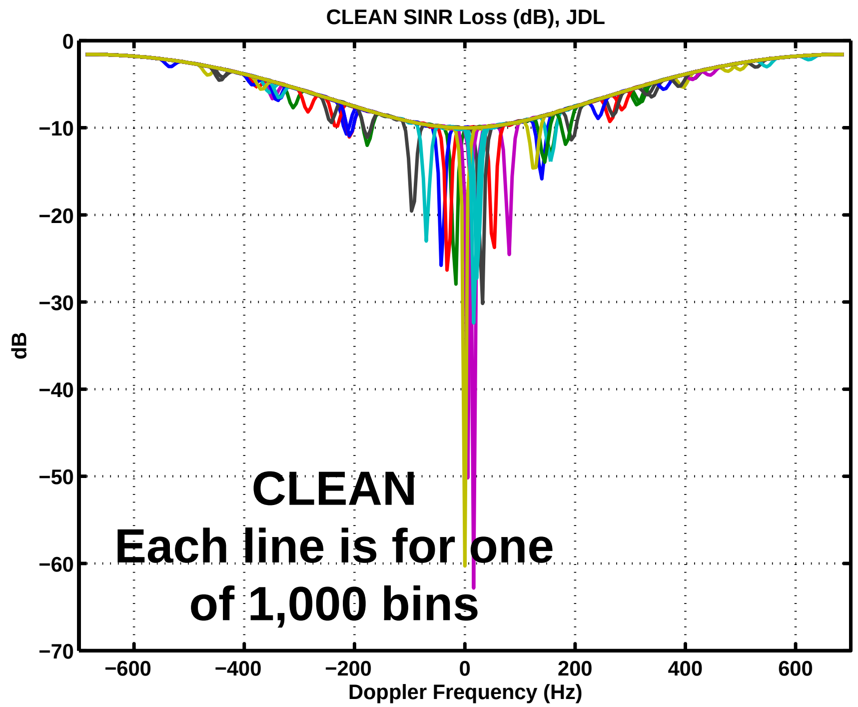
- Baseline processing
  - EFA, 3 Doppler bins
  - 100-bin sliding window
  - Exclude CUT and guard cells from training



- CLEAN plus PCT
  - PCT used 10 tiles of 100 bins each
  - CLEAN ran until all OS-CFAR detections removed ⇒ 50 iterations
  - Meets PFA of ~1x10^{-5} at ~15 dB threshold

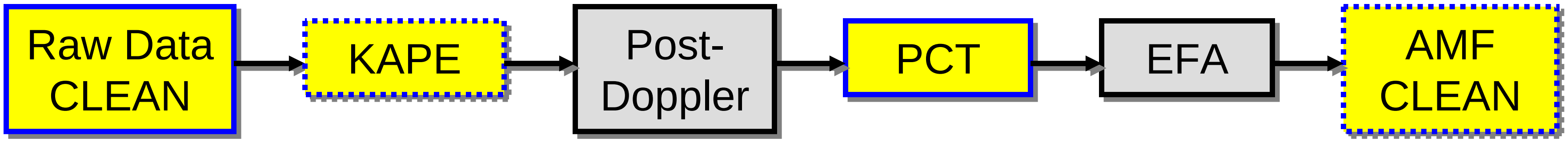
SINR Losses due to PCT & CLEAN





- Local training and PCT both used 100 bins
  - PCT increased <u>average</u> loss less than 1 dB
- CLEAN operated on only 50 bins
  - Manifested as highly-localized SINR-loss nulls
  - CLEAN increased <u>average</u> SINR loss about 0.1 dB

Summary



- GTRI's KASSPER architecture "accommodates" four different approaches to discrete mitigation
  - Raw data CLEAN, KAPE, PCT, AMF CLEAN
  - PCT and CLEAN complement one another
- Summary of knowledge sources used by CLEAN
  - Long-dwell (SAR) data
  - Array calibration
  - Array pointing vector and absolute power calibration to distinguish targets from discretes
  - KA-generated $\mathbf{R}$ for MLE CLEAN (primarily the importance stage)
- CLEAN knowledge products
  - Array calibration (Phase Gradient Autofocus approach)
  - Clutter angle-Doppler support

Future Work

- Examine performance of techniques on standard data sets
  - KASSPER Data Cubes
  - TUXEDO (Camp Navajo)
- Evaluate relative benefits of the techniques
  - Both stand-alone and in combination
  - Down-select for final configuration
    - KAPE is a given, so the question will be:
    - What are the benefits of CLEAN, PCT, and AMF CLEAN, and what is their impact on processor, memory, and latency???
- CLEAN variations
  - Impact on area coverage rate of angle blanking (instead of nulling)
  - Decomposition that is more accurate, lower order, and efficient
    - Frequency dithering (SCHISM), RELAX, etc.
  - Parametric impulse response for flashes, etc.