Knowledge-Assisted STAP Analysis Using Measured Airborne Radar Data

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Outline

- Background
  - Objectives of aerospace radar STAP
  - STAP's limiting factors
- A taxonomy of space-time clutter heterogeneity
- Impact of clutter heterogeneity on STAP performance
- Examples of clutter heterogeneity in the Multi-Channel Airborne Radar Measurements (MCARM) database
- Knowledge-Assisted STAP
  - Overview
  - KA-STAP examples
- KA-STAP implementation issues

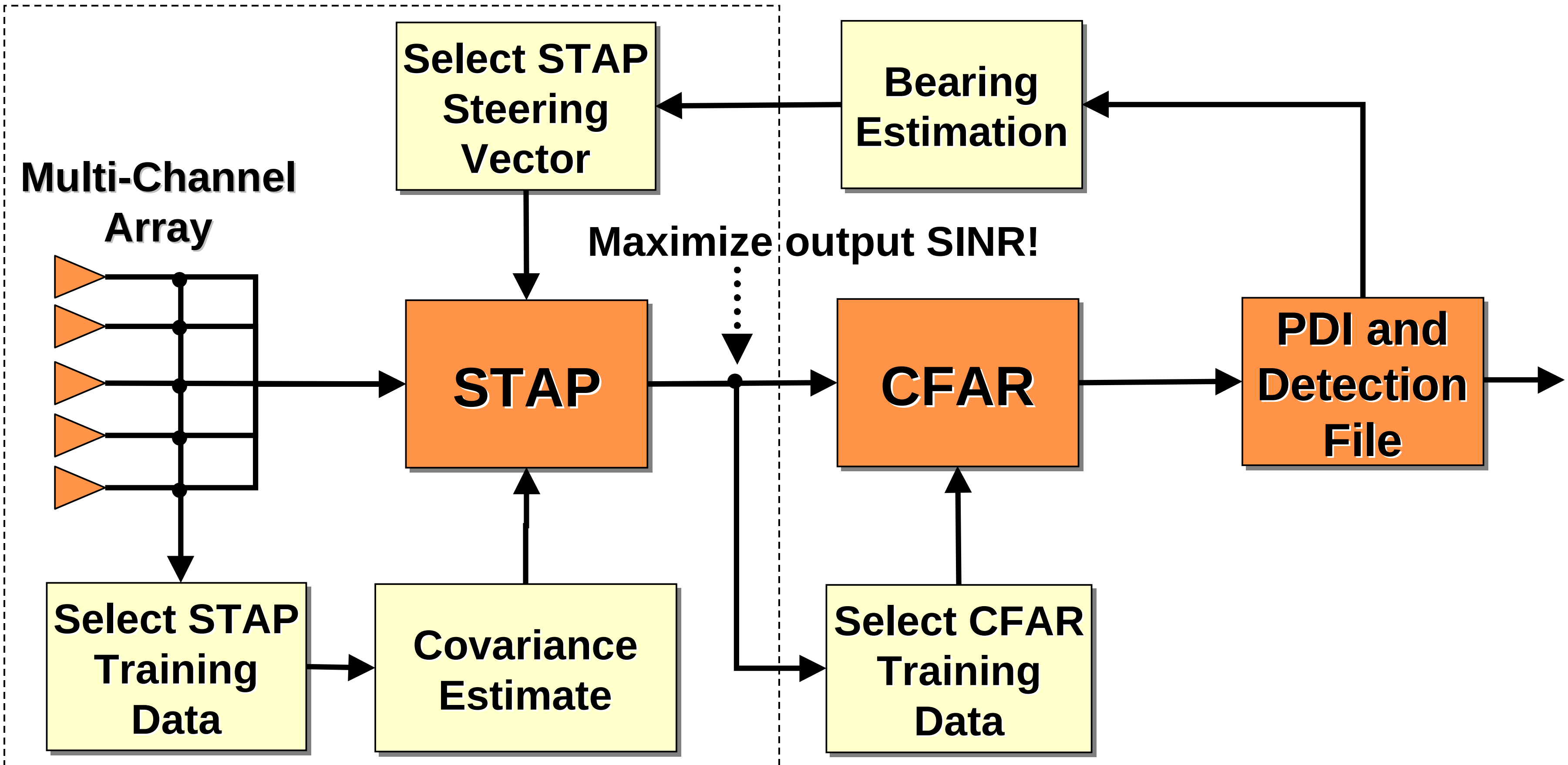
Goals of STAP

- Significantly improve detection of “weak” targets
  - Low RCS and/or slow-moving targets
    - Endo-clutter detection
- Overcome diffraction-limited system performance
  - STAP is a member of the class of super-resolution algorithms
- Provide more effective use of radar system resources
  - Enhance search rates by minimizing dwell time

F-22 (Courtesy Lockheed)

“Traditional” STAP in Aerospace Radar

- Exploit digital signal processing capability and advanced algorithms to improve automatic detection and bearing estimation of surface and airbreathing threats
  - Stringent requirements (clutter, jamming); “Mass for MIPs” paradigm



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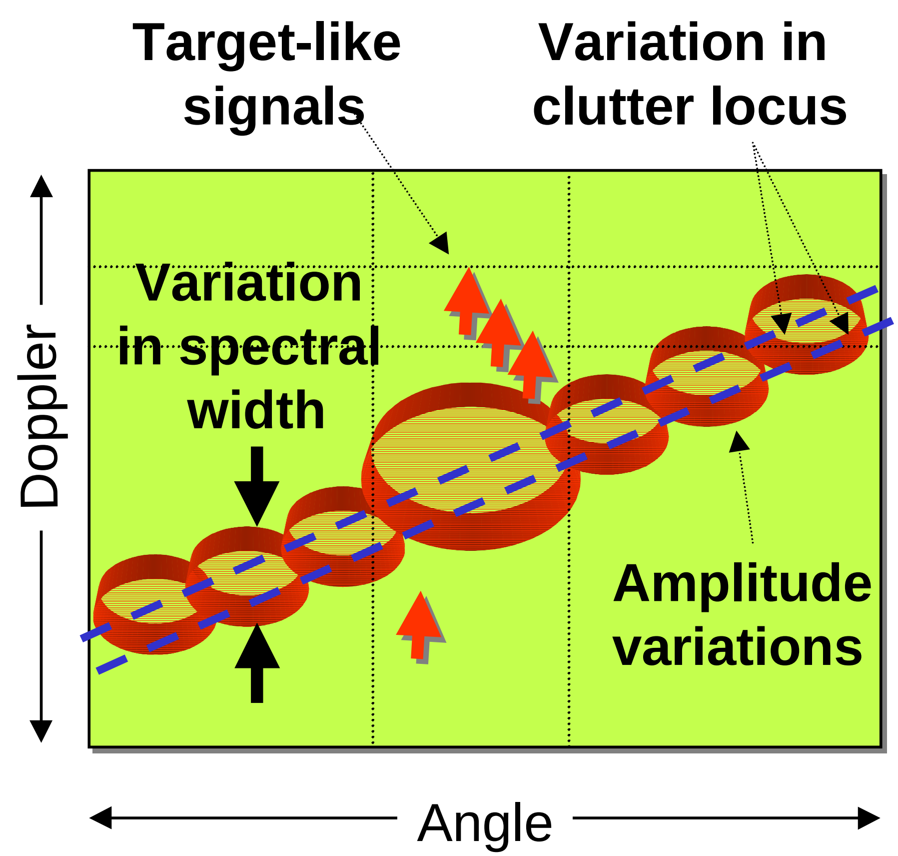
Limiting Factors on STAP Performance

- System design
  - Subarraying, A/D bits, timing errors, channel match, non-dispersive errors, etc.
- Nonstationarity [1-5]
  - Variation in angle-Doppler loci due to sensor geometry
    - Bistatics, space-based radar, non-sidelooking and nonlinear arrays
    - Antenna pattern taper
      - Space-based radar
- Clutter heterogeneity [6-9]
  - Variation in space-time clutter behavior over range as a result of changing cultural features

Heterogeneity and Nonstationarity



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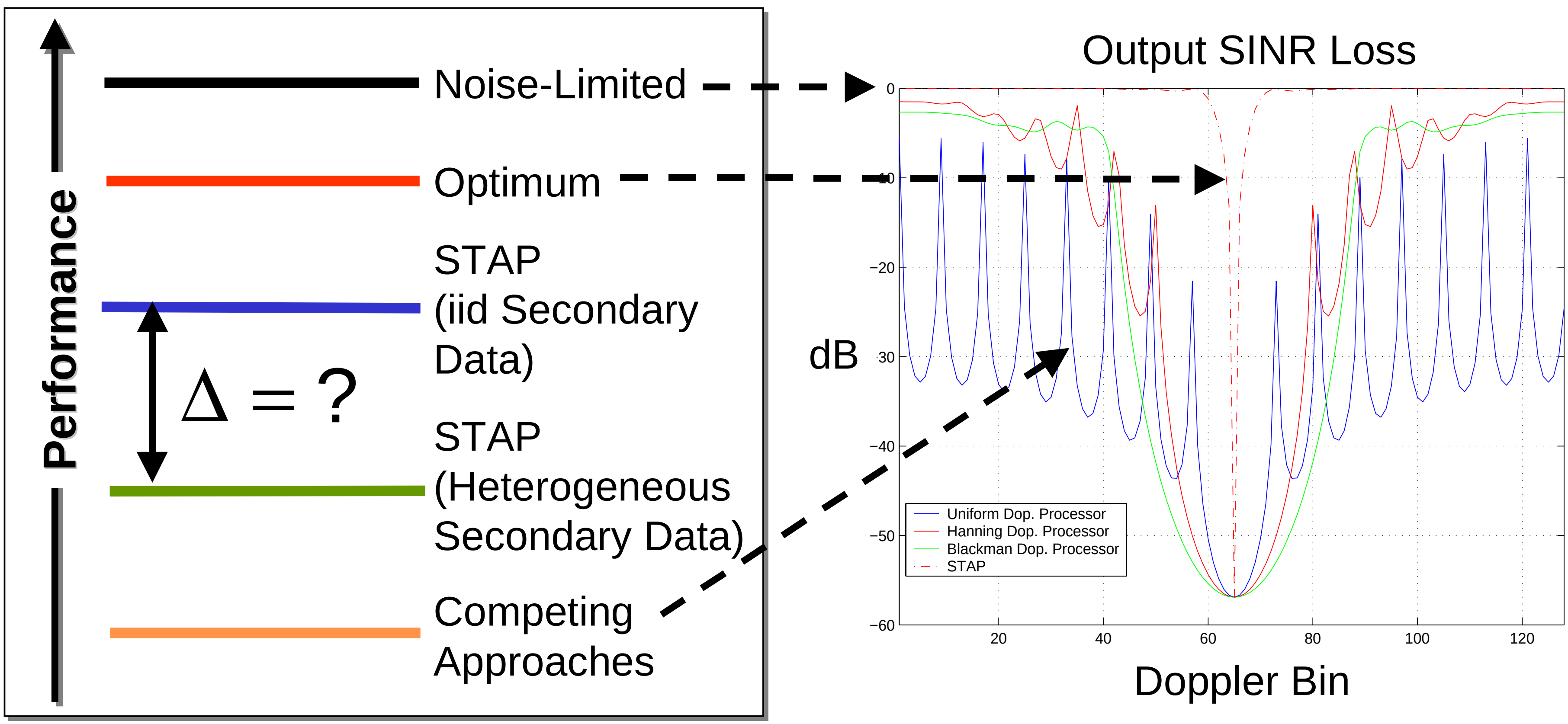
Performance Expectations

Ideal Airborne Radar
Interference Mitigation Example



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Generic (Space-Time) Signal Processor

$$\mathbf{X}_{\mathbf{k}} = \begin{pmatrix} [\mathbf{X}_{\mathbf{k}}]_{1,1} & [\mathbf{X}_{\mathbf{k}}]_{1,2} & \cdots & [\mathbf{X}_{\mathbf{k}}]_{1,N} \\ [\mathbf{X}_{\mathbf{k}}]_{2,1} & [\mathbf{X}_{\mathbf{k}}]_{2,2} & \cdots & [\mathbf{X}_{\mathbf{k}}]_{2,N} \\ | & | & \cdots & | \\ [\mathbf{X}_{\mathbf{k}}]_{M,1} & [\mathbf{X}_{\mathbf{k}}]_{M,2} & \cdots & [\mathbf{X}_{\mathbf{k}}]_{M,N} \end{pmatrix} \longrightarrow \boxed{vec(\mathbf{X}_{\mathbf{k}})} \xrightarrow{\mathbf{x}_{\mathbf{k}}} \boxed{\mathbf{w}_{\mathbf{k}}} \longrightarrow y_k = \mathbf{w}_{\mathbf{k}}^H \mathbf{x}_{\mathbf{k}}$$

$$SINR = \frac{\text{Signal Power}}{\text{Interference + Noise Power}} = \frac{E\left[y_{k/s} y_{k/s}^*\right]}{E\left[y_{k/H_0} y_{k/H_0}^*\right]} = \frac{\mathbf{w}_{\mathbf{k}}^H \mathbf{R}_{\mathbf{k/s}} \mathbf{w}_{\mathbf{k}}}{\mathbf{w}_{\mathbf{k}}^H \mathbf{R}_{\mathbf{k/H_0}} \mathbf{w}_{\mathbf{k}}};$$

$$\mathbf{R}_{\mathbf{k/H_0}} = E\left[\mathbf{x}_{\mathbf{k/H_0}} \mathbf{x}_{\mathbf{k/H_0}}^H\right] = \text{ Clairvoyant Interference+Noise Covariance Matrix;}$$

$$\mathbf{R}_{\mathbf{k/s}} = E\left[\mathbf{x}_{\mathbf{k/s}} \mathbf{x}_{\mathbf{k/s}}^H\right] = \text{ Signal Covariance Matrix;}$$

$$L_{s,2} = \frac{\left.\text{SINR}\right|_{\hat{\mathbf{w}}_{\mathbf{k}}}}{\left.\text{SINR}\right|_{\mathbf{w}_{\mathbf{k/opt}}}} = \left(\frac{\hat{\mathbf{w}}_{\mathbf{k}}^H \mathbf{R}_{\mathbf{k/s}} \hat{\mathbf{w}}_{\mathbf{k}}}{\hat{\mathbf{w}}_{\mathbf{k}}^H \mathbf{R}_{\mathbf{k/H_0}} \hat{\mathbf{w}}_{\mathbf{k}}}\right) \Big/ \left(\frac{\mathbf{w}_{\mathbf{k/opt}}^H \mathbf{R}_{\mathbf{k/s}} \mathbf{w}_{\mathbf{k/opt}}}{\mathbf{w}_{\mathbf{k/opt}}^H \mathbf{R}_{\mathbf{k/H_0}} \mathbf{w}_{\mathbf{k/opt}}}\right);$$

$$\boxed{\mathbf{w}_{\mathbf{k/opt}} = \mu \mathbf{R}_{\mathbf{k}}^{-1} \mathbf{s}_{\mathbf{s\text{-}t}} \quad \text{versus} \quad \hat{\mathbf{w}}_{\mathbf{k}} = \beta \hat{\mathbf{R}}_{\mathbf{k}}^{-1} \mathbf{v}_{\mathbf{s\text{-}t}}\ .}$$

Adaptive Versus Optimal Performance

Adaptive: Generally assumes IID training data

	Train	Apply	Train	

Range

$$\hat{\mathbf{R}}_{\mathbf{k}} = ?!$$

$$\hat{\mathbf{R}}_{\mathbf{k}} = \frac{1}{L}\sum_{m=1}^{L} \mathbf{x}_{\mathbf{m}}\mathbf{x}_{\mathbf{m}}^{H}$$

Maximum Likelihood Estimation *a la* RMB Rule (2xDoF rule)

$$\mathbf{x}_{\mathbf{k}} \rightarrow \hat{\mathbf{w}}_{\mathbf{k}} = \hat{\mathbf{R}}_{\mathbf{k}}^{-1}\mathbf{v}_{\mathbf{s-t}} \rightarrow \hat{y}_k$$

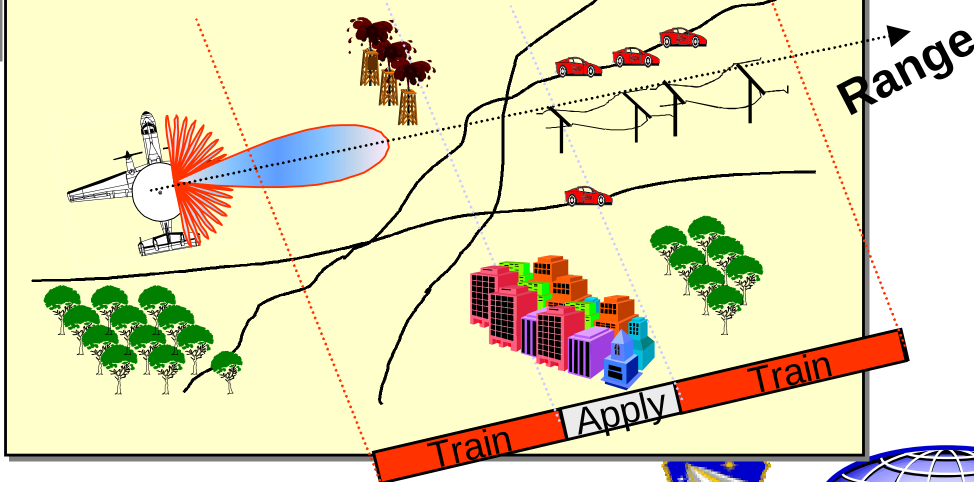
$$\mathbf{x}_{\mathbf{k}} \quad \mathbf{R}_{\mathbf{k}} = \text{known}$$

$$\mathbf{w}_{\mathbf{k}} = \mathbf{R}_{\mathbf{k}}^{-1}\mathbf{s}_{\mathbf{s-t}}$$

$$y_k$$

Optimum: Known clutter statistics

Heterogeneous Clutter Environment



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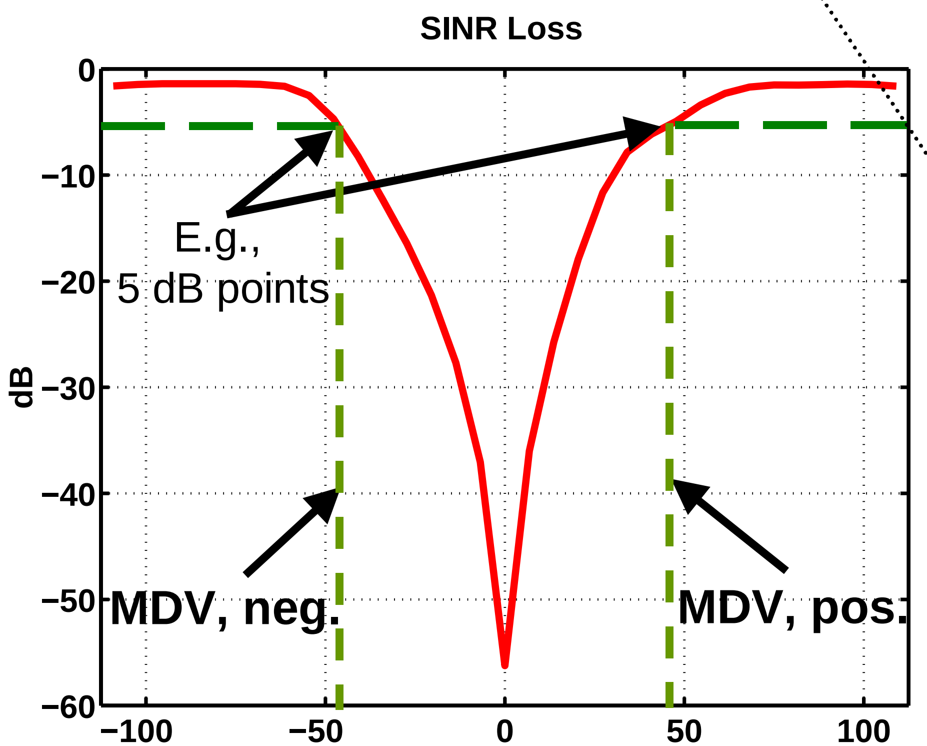
Measures of Performance

- In the Gaussian case, SINR relates directly to P_D and P_{FA}
  - Convenient and instructive to consider SINR Loss as a key metric

$$SINR\left(\gamma_s, \tilde{f}_d\right) = \underbrace{SNR(\gamma_s)} \cdot \underbrace{L_{s,1}(\gamma_s, \tilde{f}_d)} \cdot \underbrace{L_{s,2}(\gamma_s, \tilde{f}_d)}$$

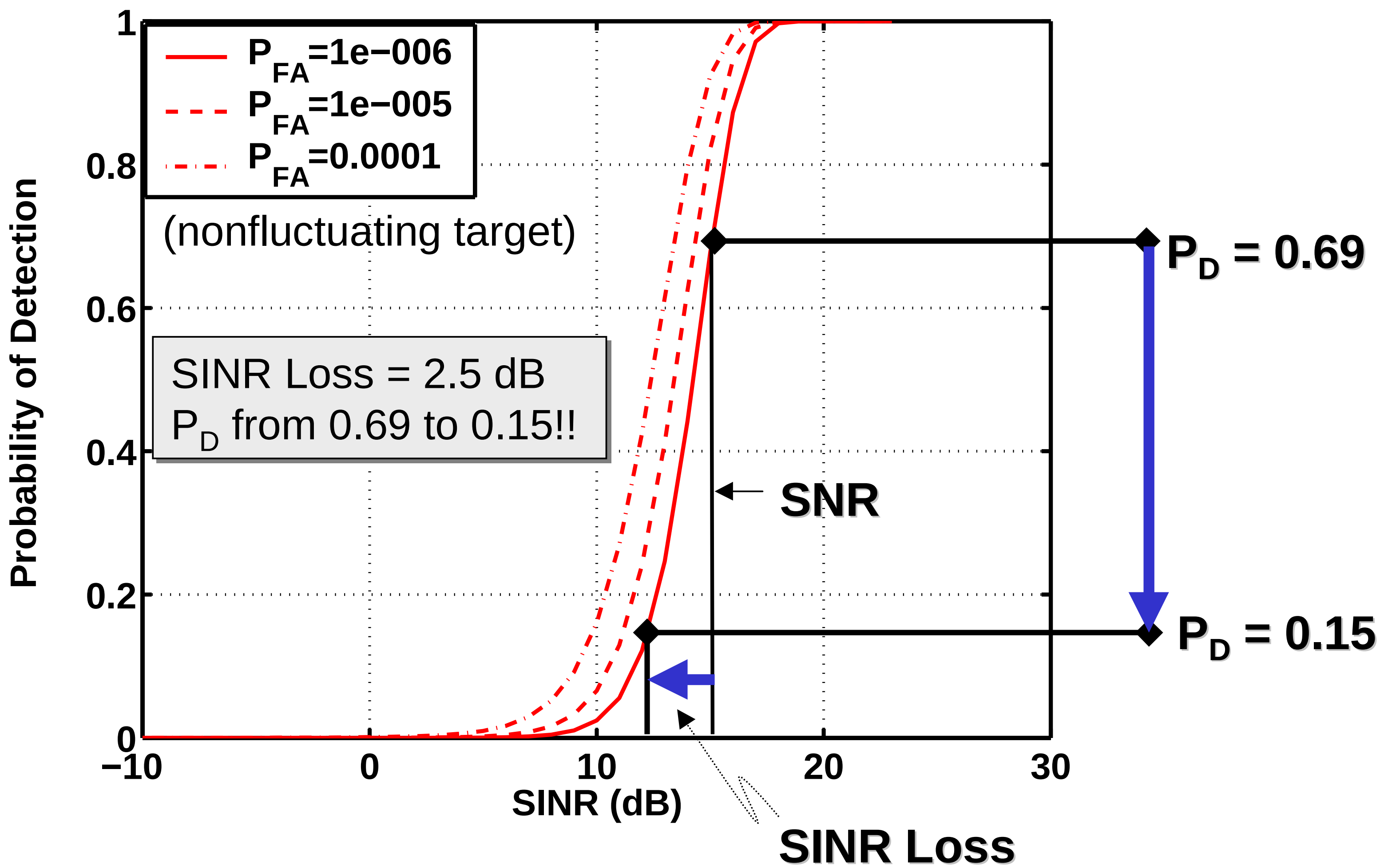


- SINR loss due to colored noise
- Determines noise-limited detection performance
- SINR degradation due to estimation losses

MDV = minimum discernible velocity

$0 \leq L_{s,1}, \ L_{s,2} \leq 1$

Relationship Between SINR and P_D



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Taxonomy of Clutter Heterogeneity [6-7]

Type	Some Causes	Impact
Amplitude	Spatially varying clutter reflectivity, shadowing, edges	Inadequately nulled clutter, increased Pfa
Spectral	Variable ICM (e.g., windswept fields, undulation of waves)	Inappropriately set filter notch, uncancelled clutter, degraded MDV
CNR-Dependent Spectral	CNR's influence on spectral spreading mechanisms	Inadequately nulled clutter, degraded MDV
Moving Scatterers	Ground/air traffic, weather	Signal cancellation, distorted beam, exhausts DoF
Some other effects	Chaff, hot clutter,multi-bounce/path	Combination of above

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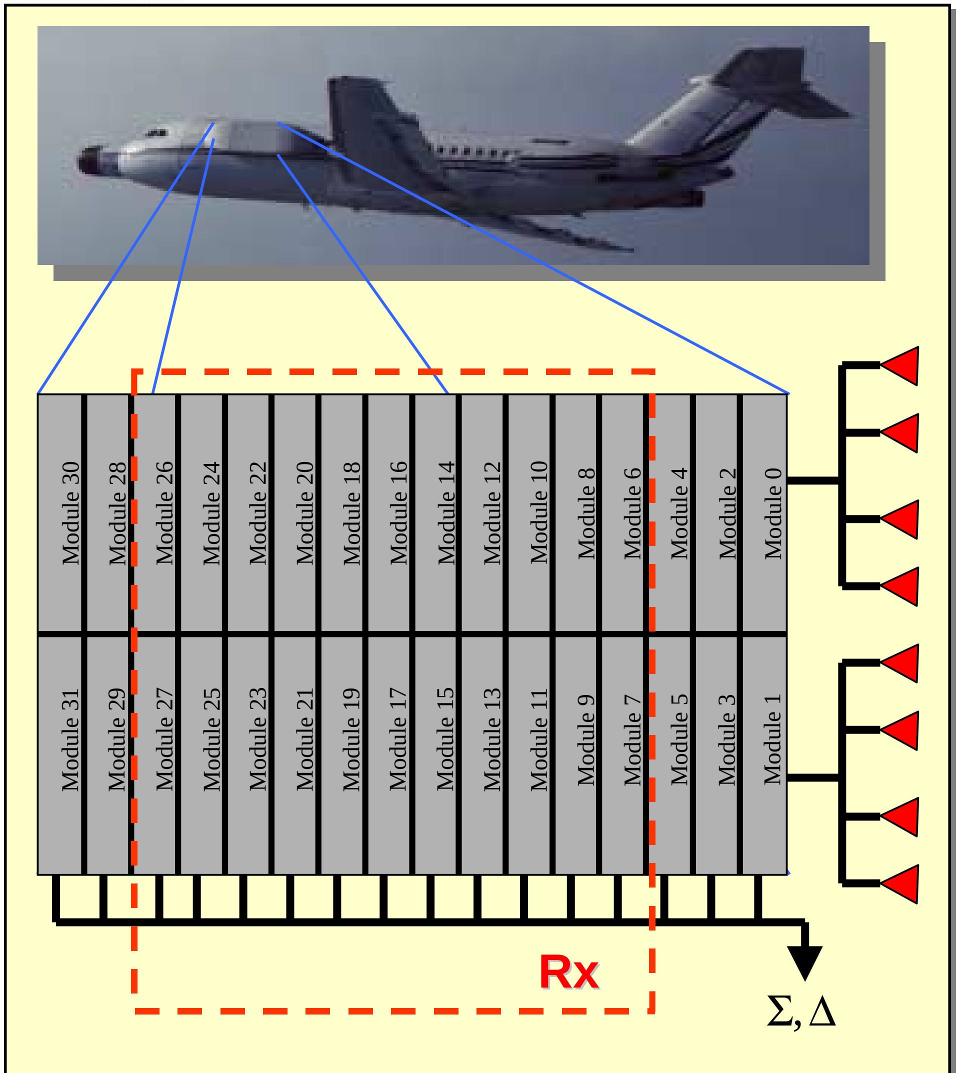
Multichannel Airborne Radar Measurements [13]



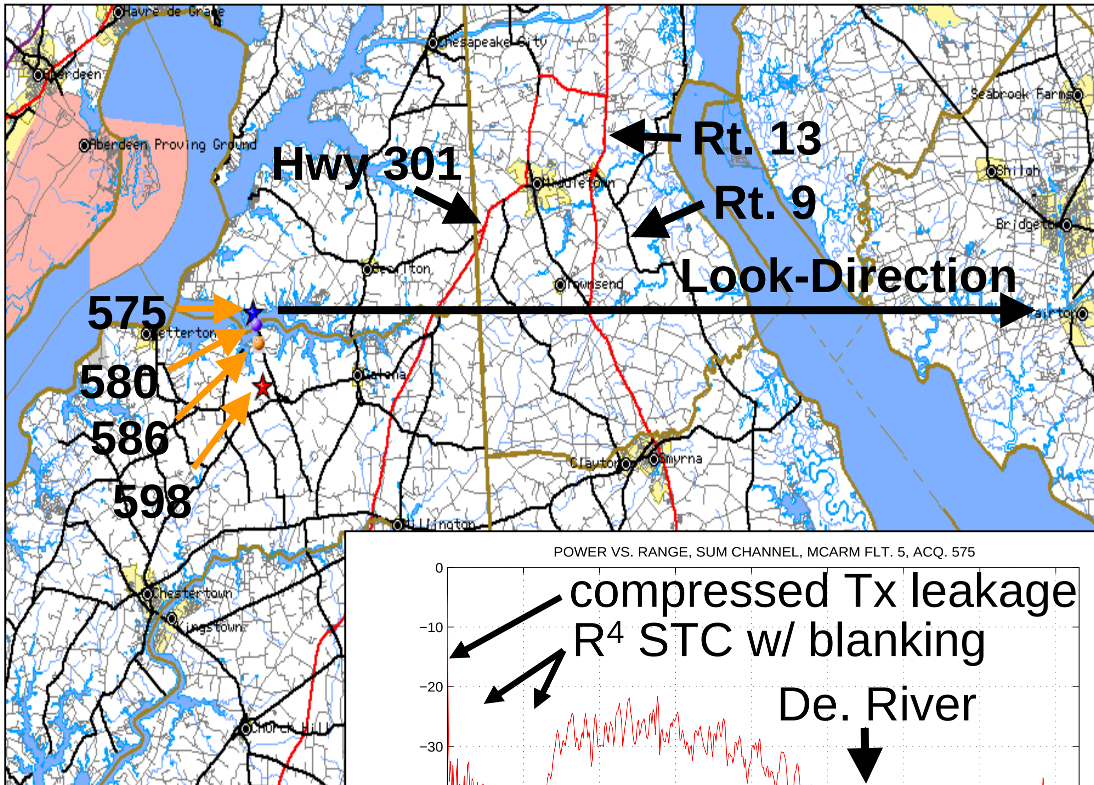
MCARM

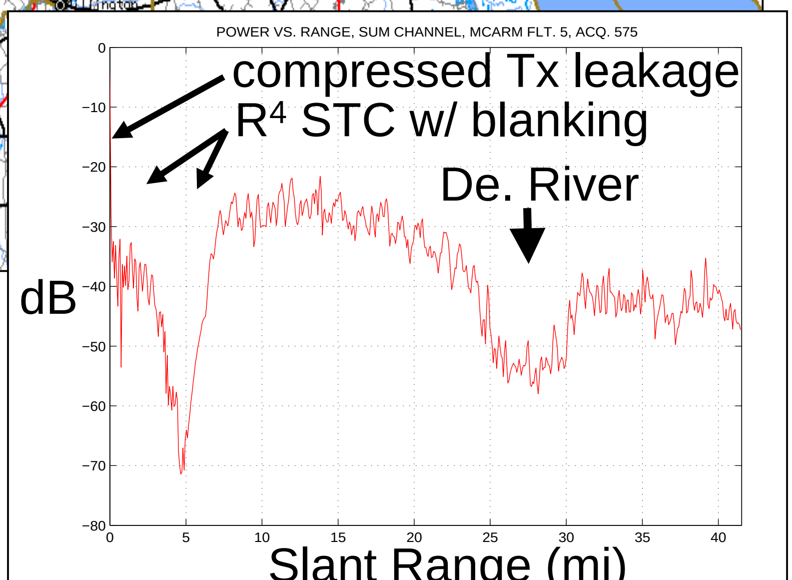
Objective: Prove the **performance potential** of STAP via airborne data collection and analysis.

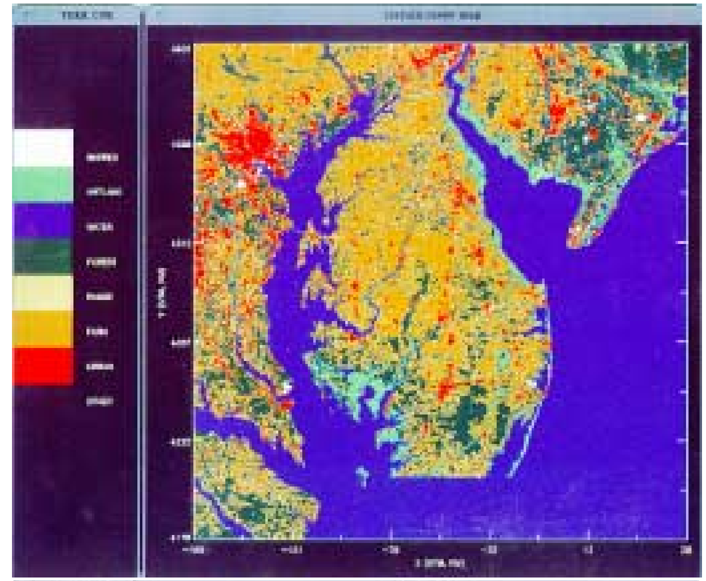
MCARM System Parameters

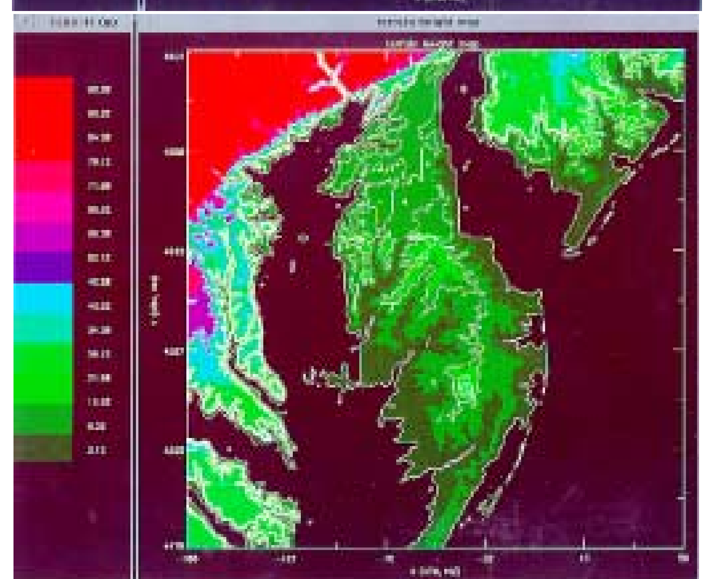
- L-band transmit frequency
- 15 kW peak transmit power
- Variable PRF (0.5kHz, 2kHz, 7kHz)
- LFM or gated-RF
- 0.8 microsecond range resolution (120 m)
- 0.8 MHz receiver bandwidth
- 7.5 degree Tx beam or "blob" (3x) pattern for broad coverage
- 1.25 MHz IF center frequency
- 5 MHz IF sampling rate (4x oversample for Digital IQ)
- Test manifold for channel balancing
- Range measured steering vectors
- 32 subarrays
- 24 receivers (sum, delta, 11 over 11 planar)
- 128 radiating elements total (32x4)
- 1 acquisition = 1 CPI

Features of Data Collection Region









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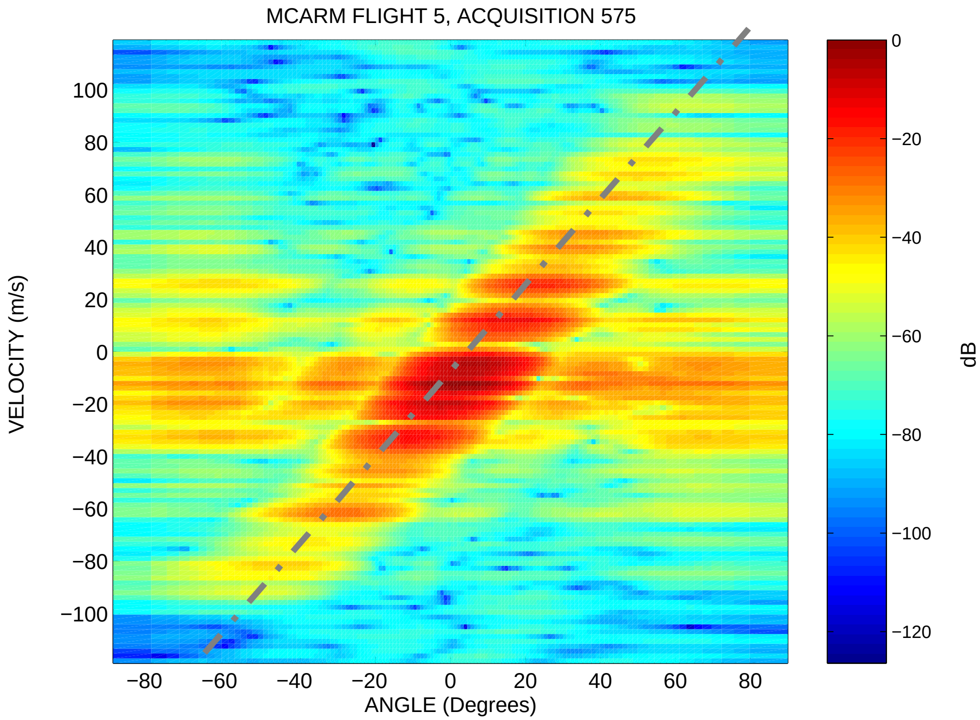
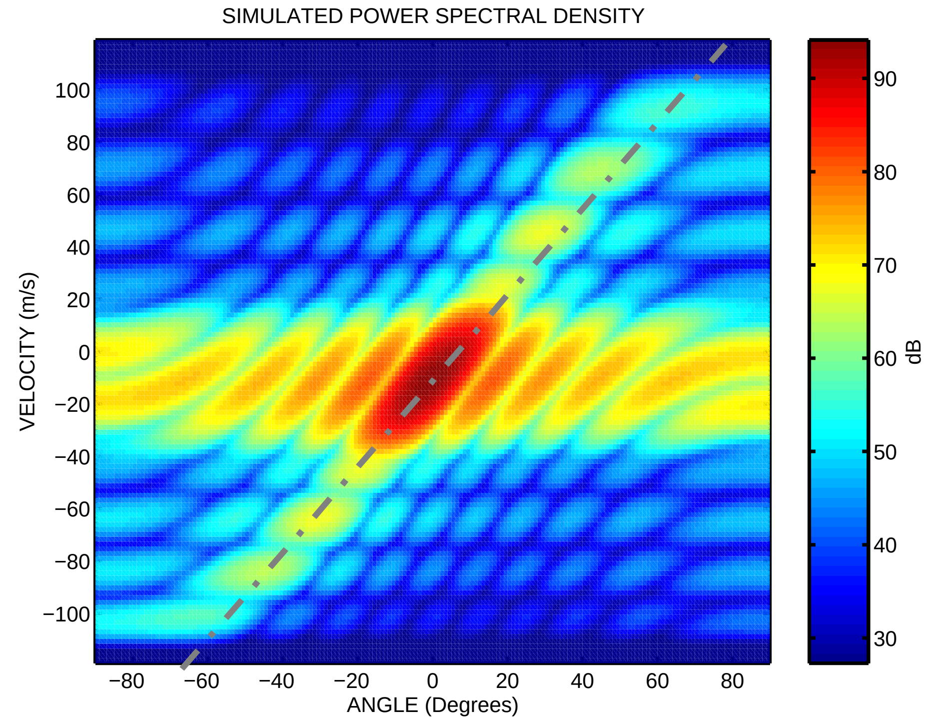
MCARM Flight 5, Acq. 575

MCARM Data, Periodogram



Simulated Data, PSD



A deterministic, highly predictable component is present...

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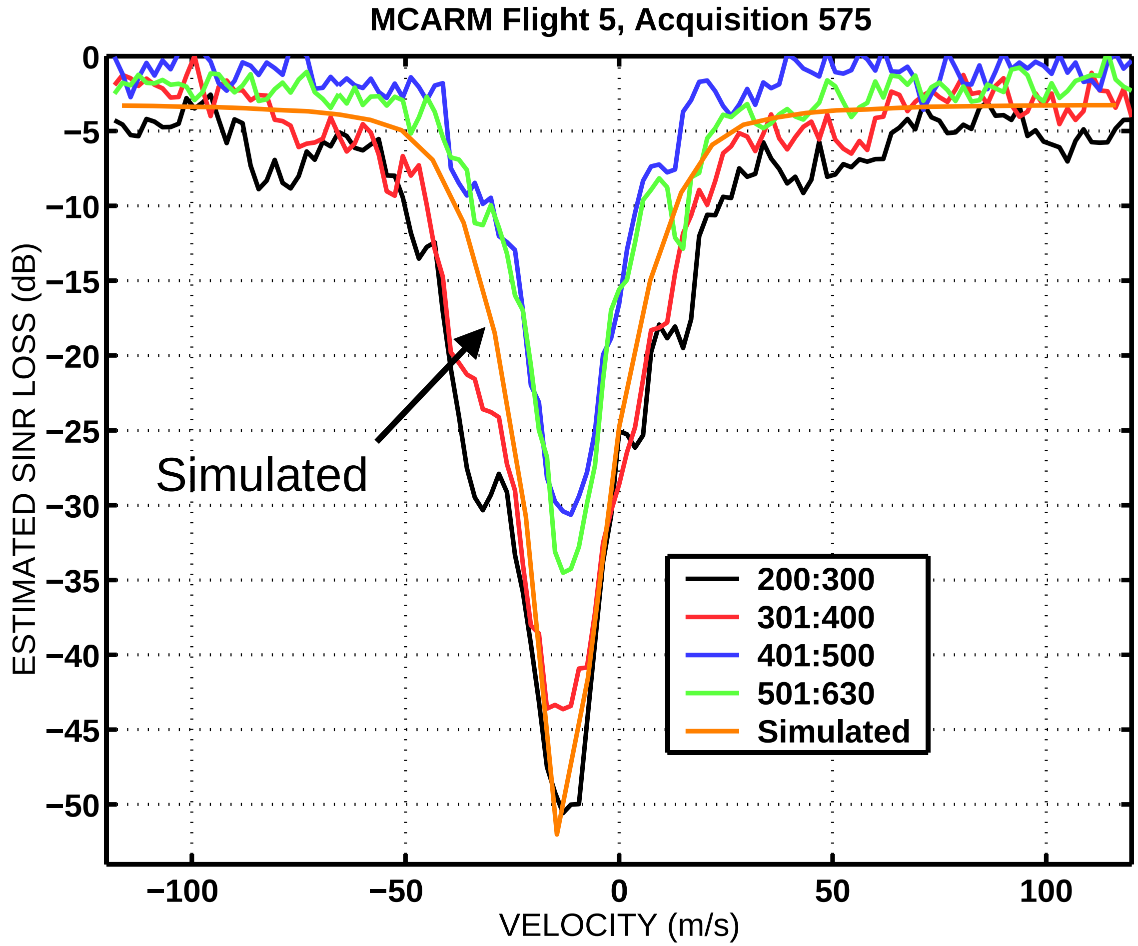
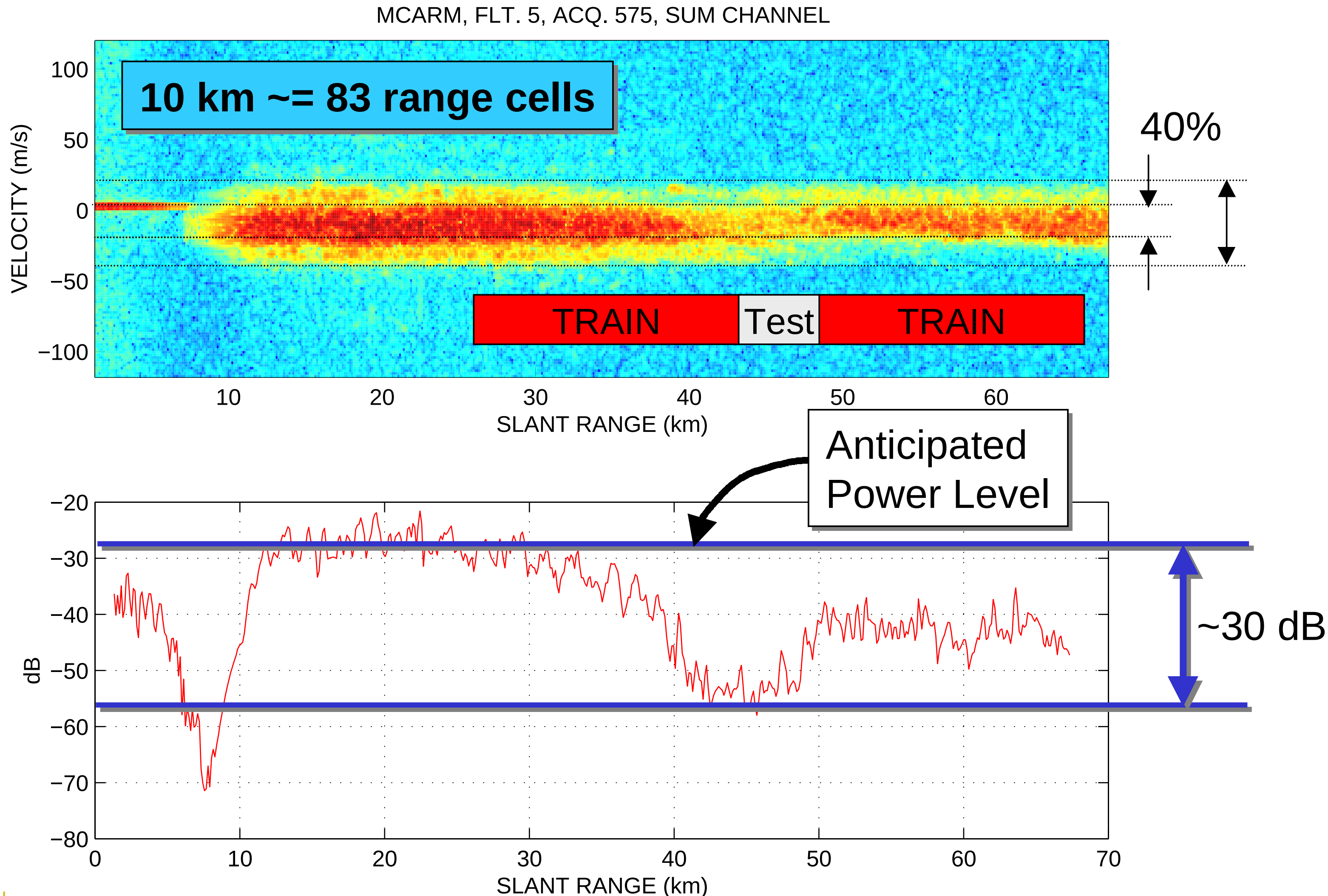
SINR Loss (MCARM Flt. 5, Acq. 575)



Simulation precisely matches MCARM mainbeam clutter Doppler frequency and relative shape. However, characteristics of measured data varies **wildly** over range!

Range-Doppler Map (MCARM Flt. 5, Acq. 575)



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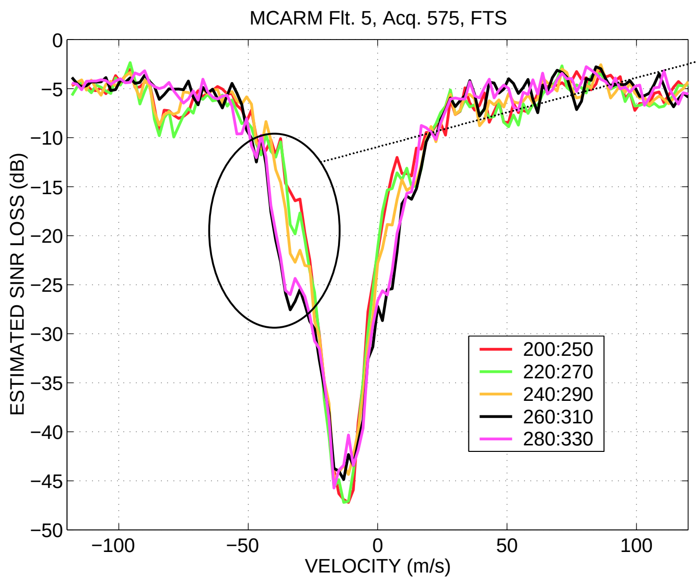
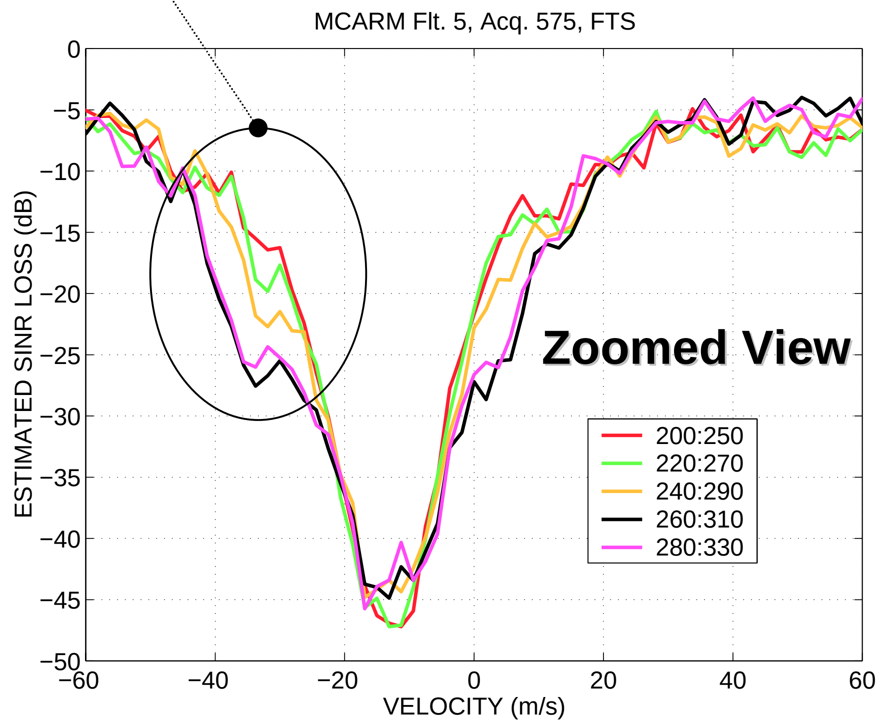
MCARM Flt. 5, Acquisition 575

SINR Loss for Varying Sample Support

- Significant SINR loss with varying sample support
- Each training window has 50 samples
- Window slides 20 samples per curve

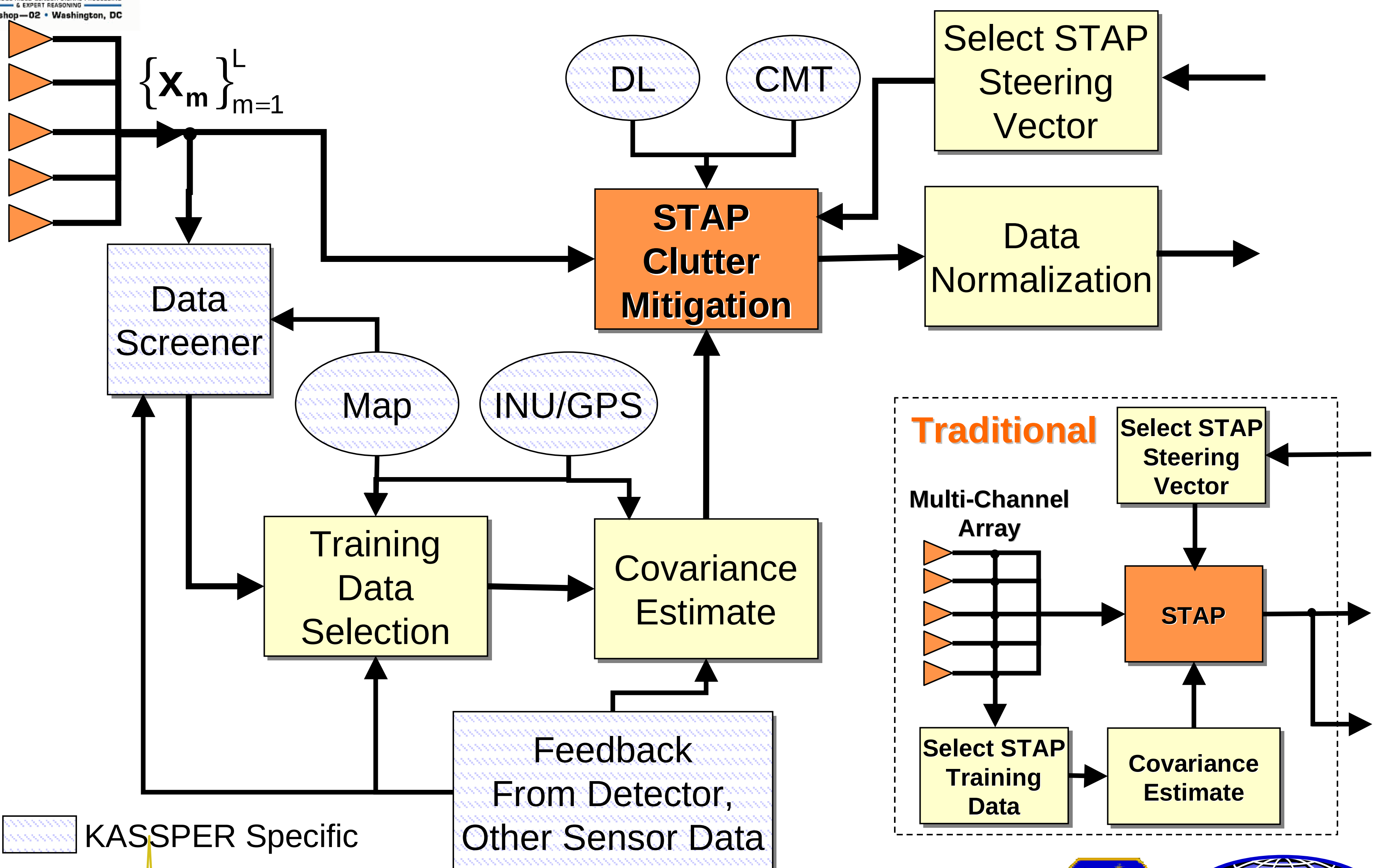




Targets in the secondary data (TSD) affect covariance estimate, lead to SINR loss...

Up to 15 dB additional loss!

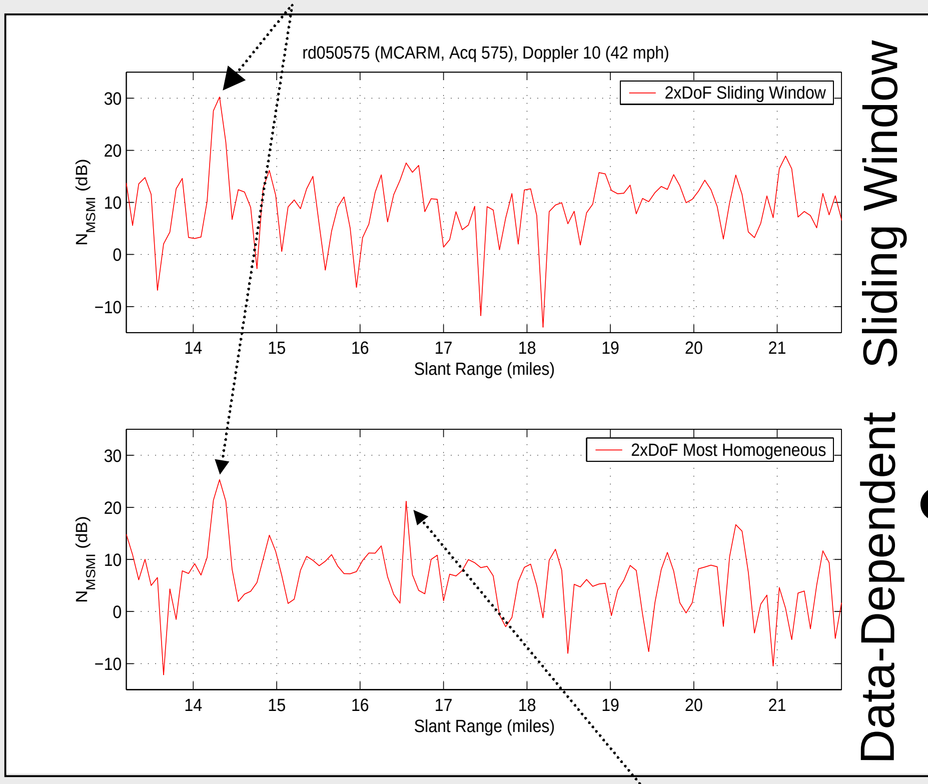
KA-STAP Architecture



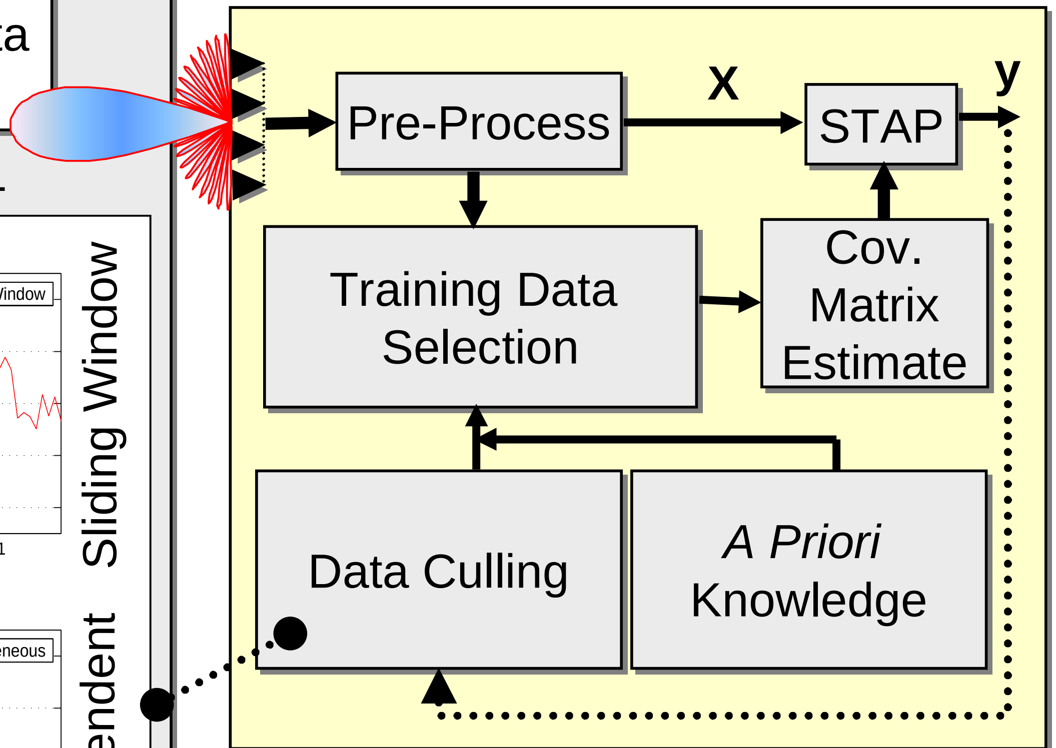
Data Dependent Training [10-11]

Careful selection of training data enables target detection!

Rt. 15 MB, Hwy 301 SL

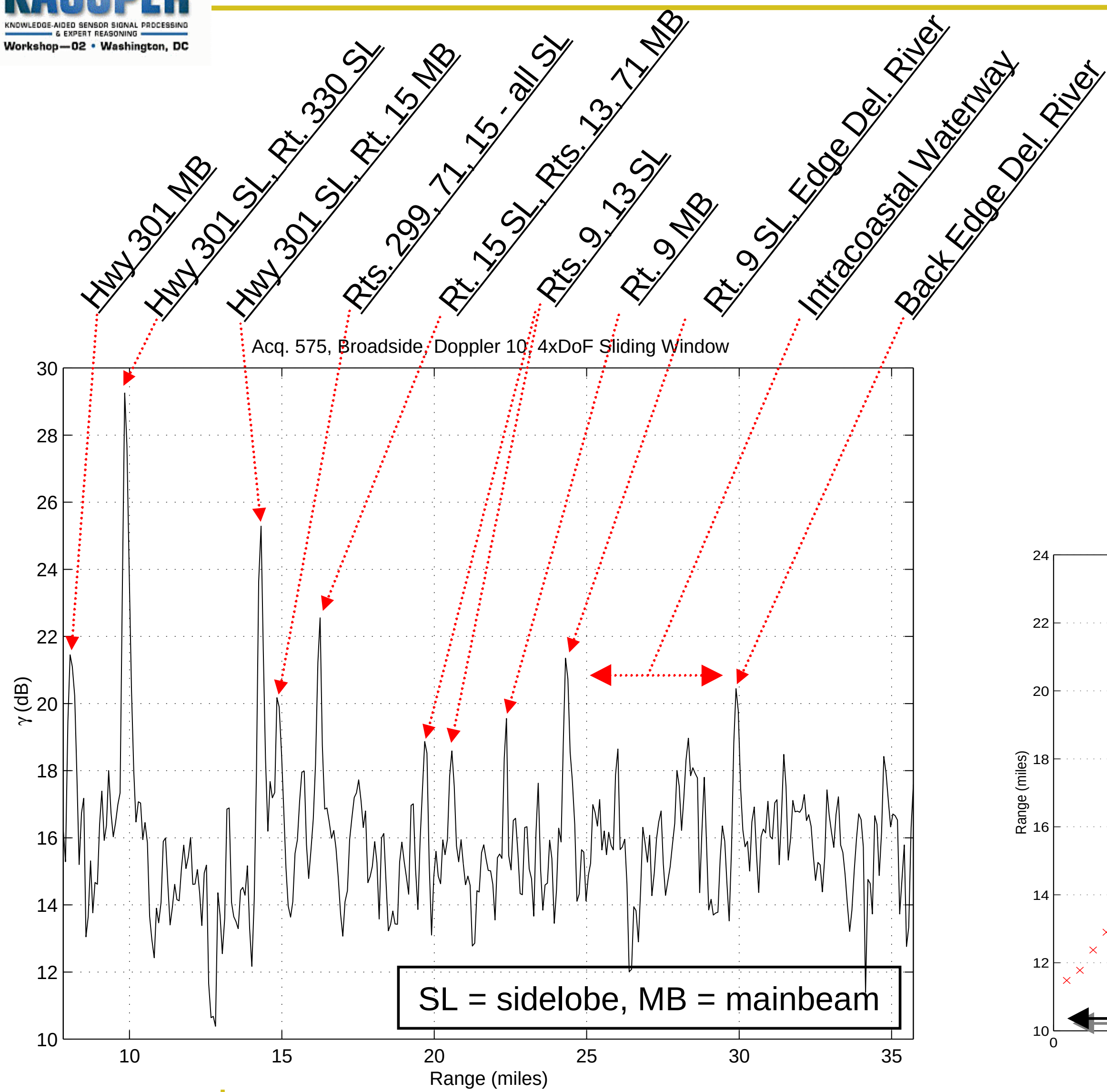


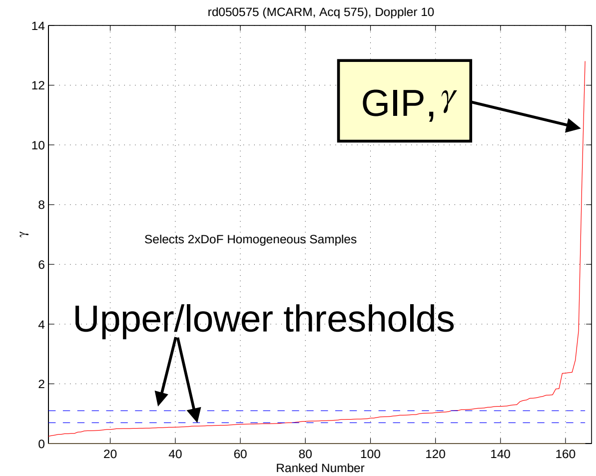
Injected target

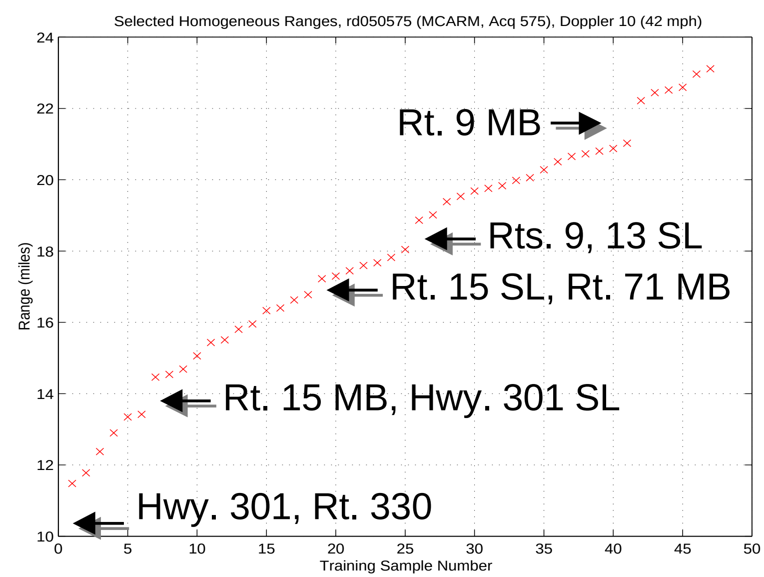


<u>Selected notes</u>: Injected target has SNR = -2.1 dB single channel/pulse (integrate 128 pulses and 22 channels); injected target signal-to-clutter ratio = -51 dB single channel/pulse.

Identifying Ground Traffic Returns

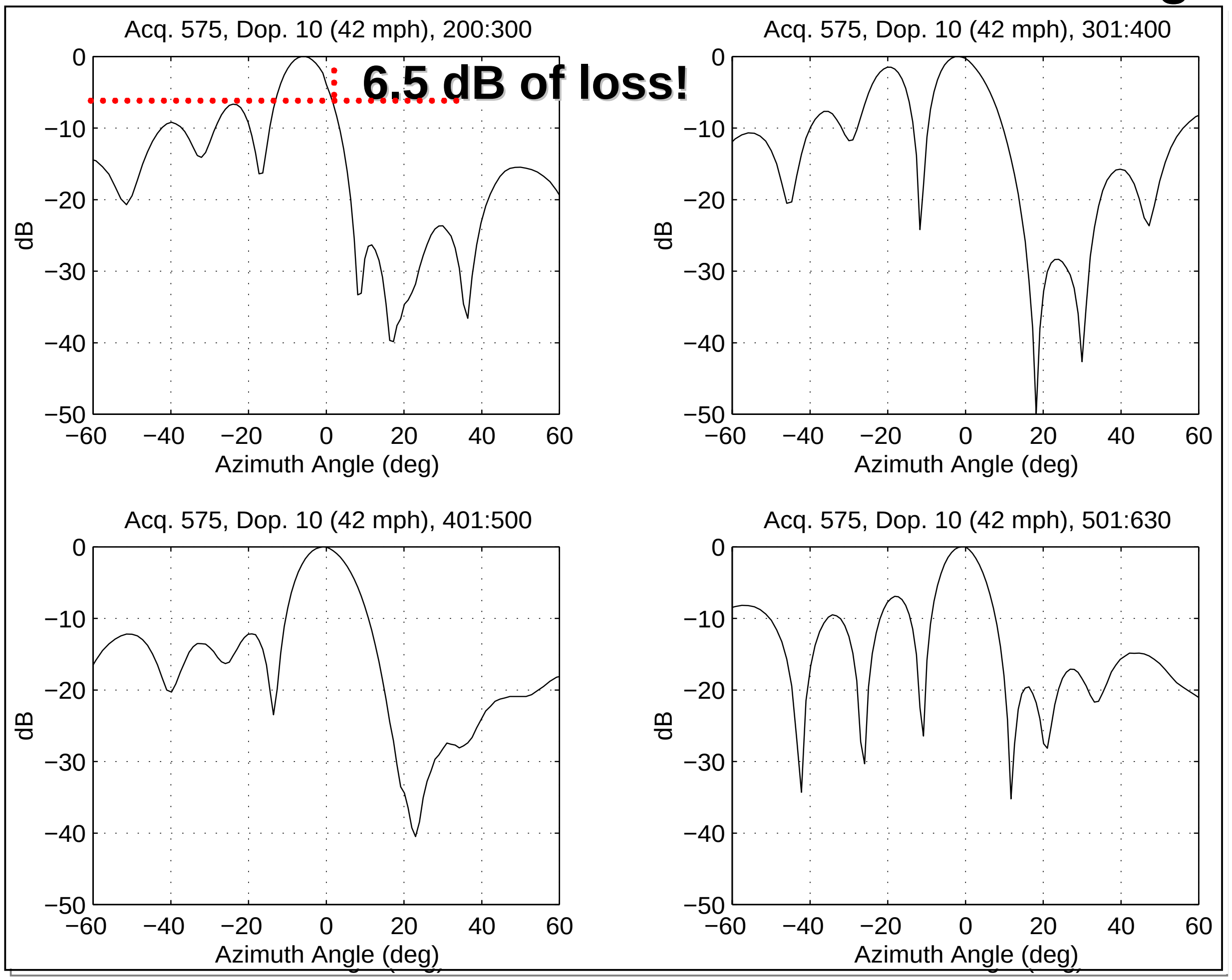






Moving Targets in Training Data

Observe "null" in look-direction of **0.9** deg.



6-8 dB SINR additional SINR loss

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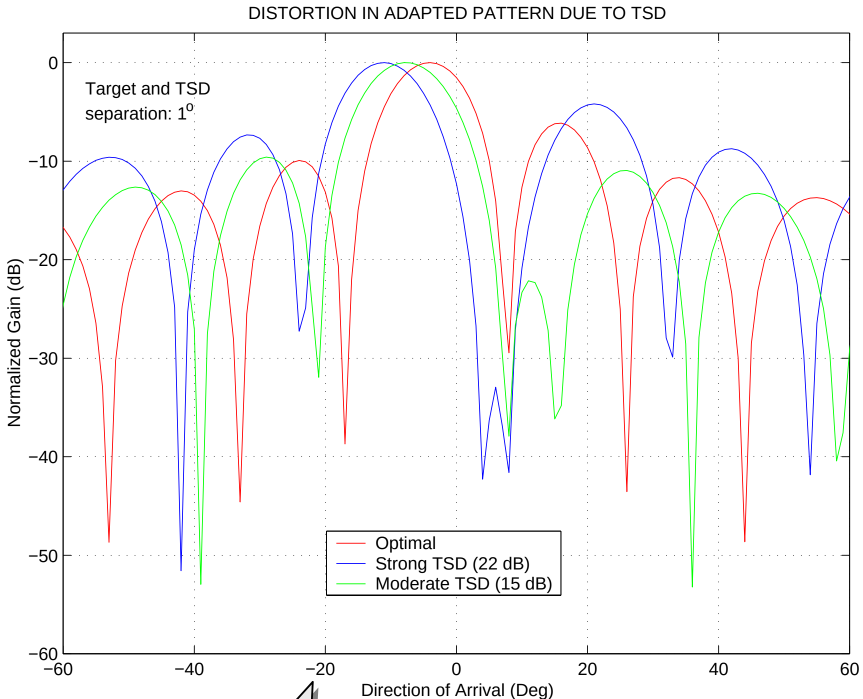
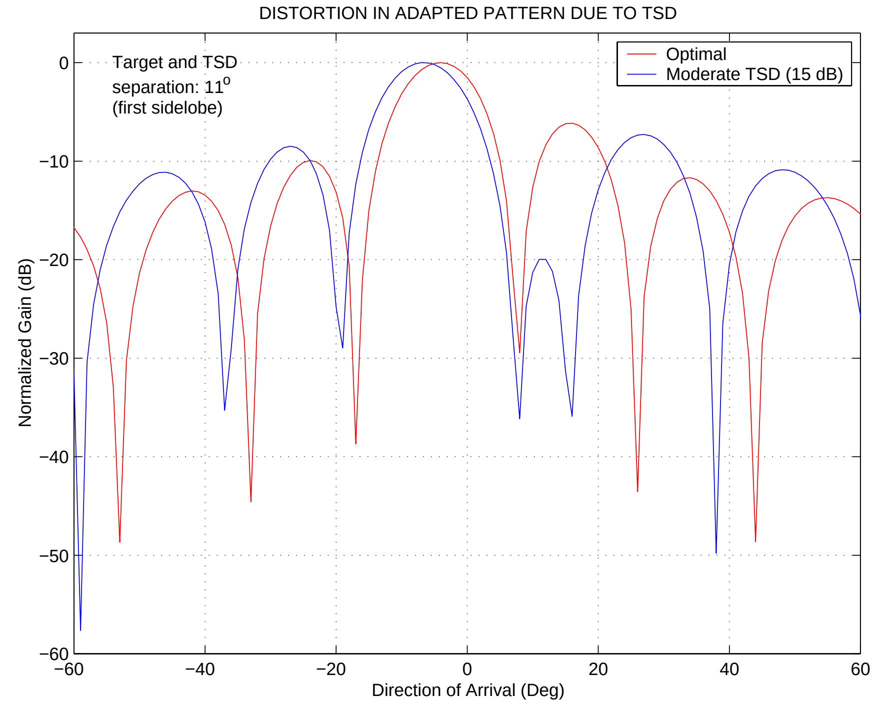
Distortion of Adaptive Pattern Due to TSD

Mainlobe



Sidelobe



Effect seen in MCARM data

$$\mathbf{w}_{k/TSD} = (1-\eta)\mathbf{w}_{opt} - \eta \mathbf{R}_k^{-1}\boldsymbol{\delta}$$

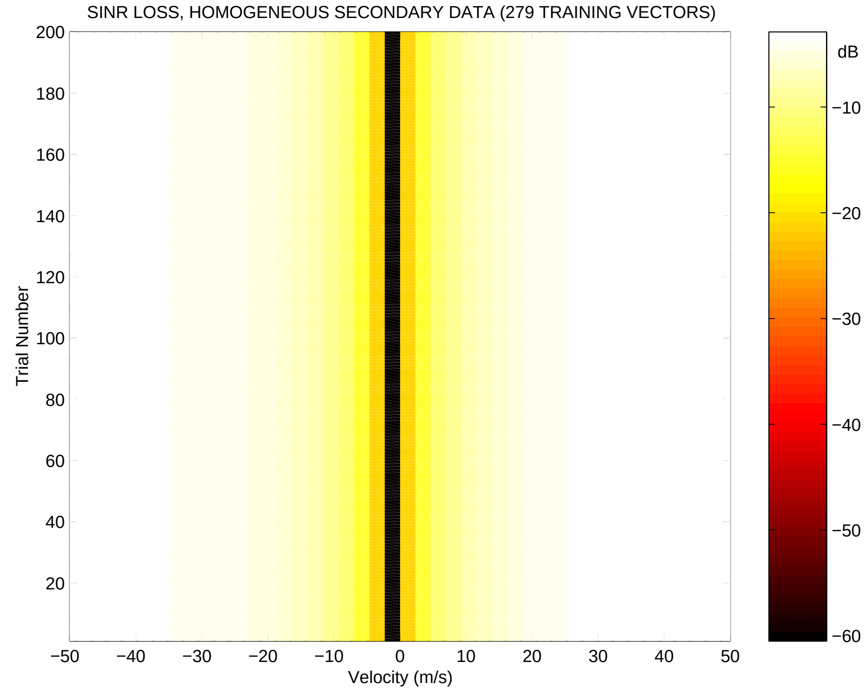
fcn(TSD Power)

Steering vector mismatch

Leads to signal cancellation

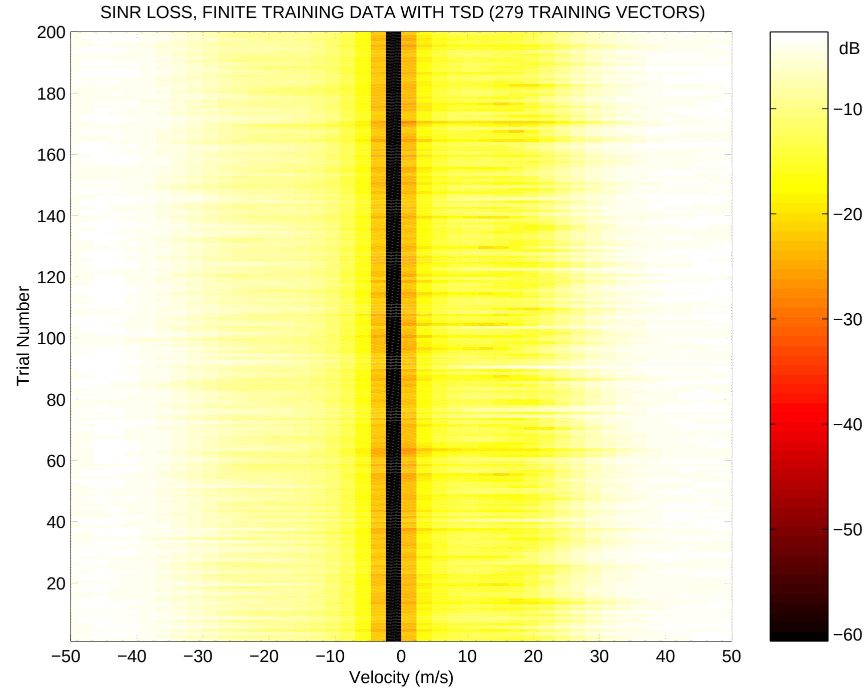
SINR Loss Using Finite Data

279 IID Secondary (Training) Vectors



- IID assumption provides upper bound on performance with finite training data
- TSD and heterogeneous clutter violate IID assumption

279 Secondary Vectors Corrupted By TSD



- 200 trials of Poisson seeding
  - TSD significantly degrades detection performance!
    - MDV increases 3x

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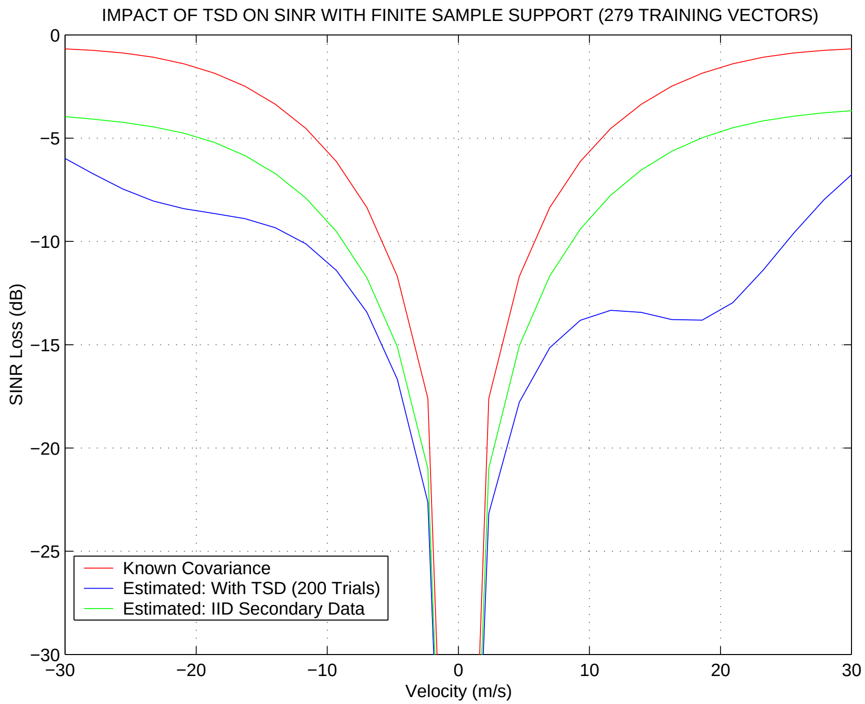
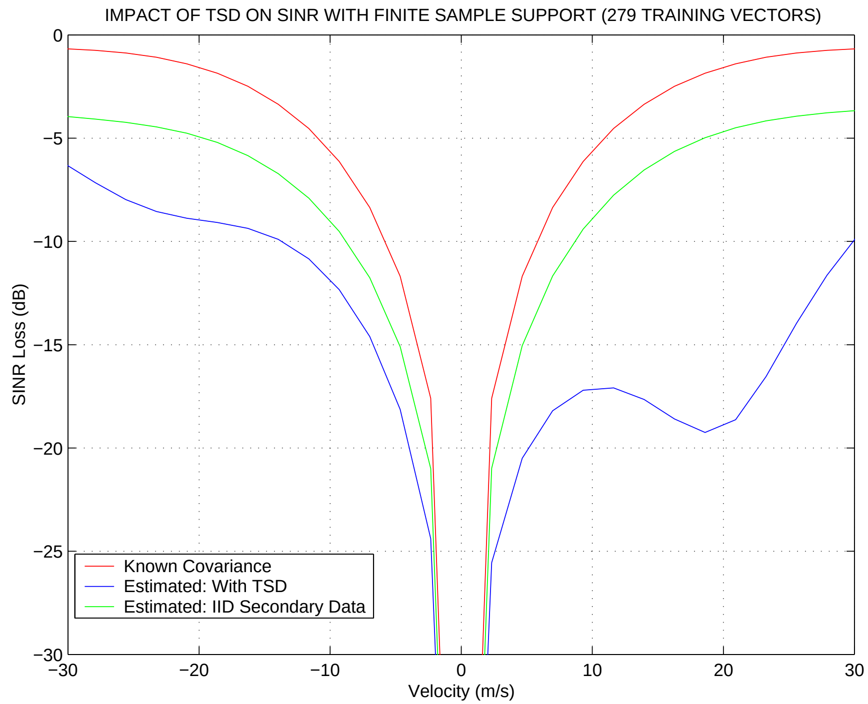
SINR Loss Comparison

Average of 200 Trials



Single Trial



Uncompensated TSD can lead to SINR loss of 15 dB…
Similar effect observed in measured MCARM data

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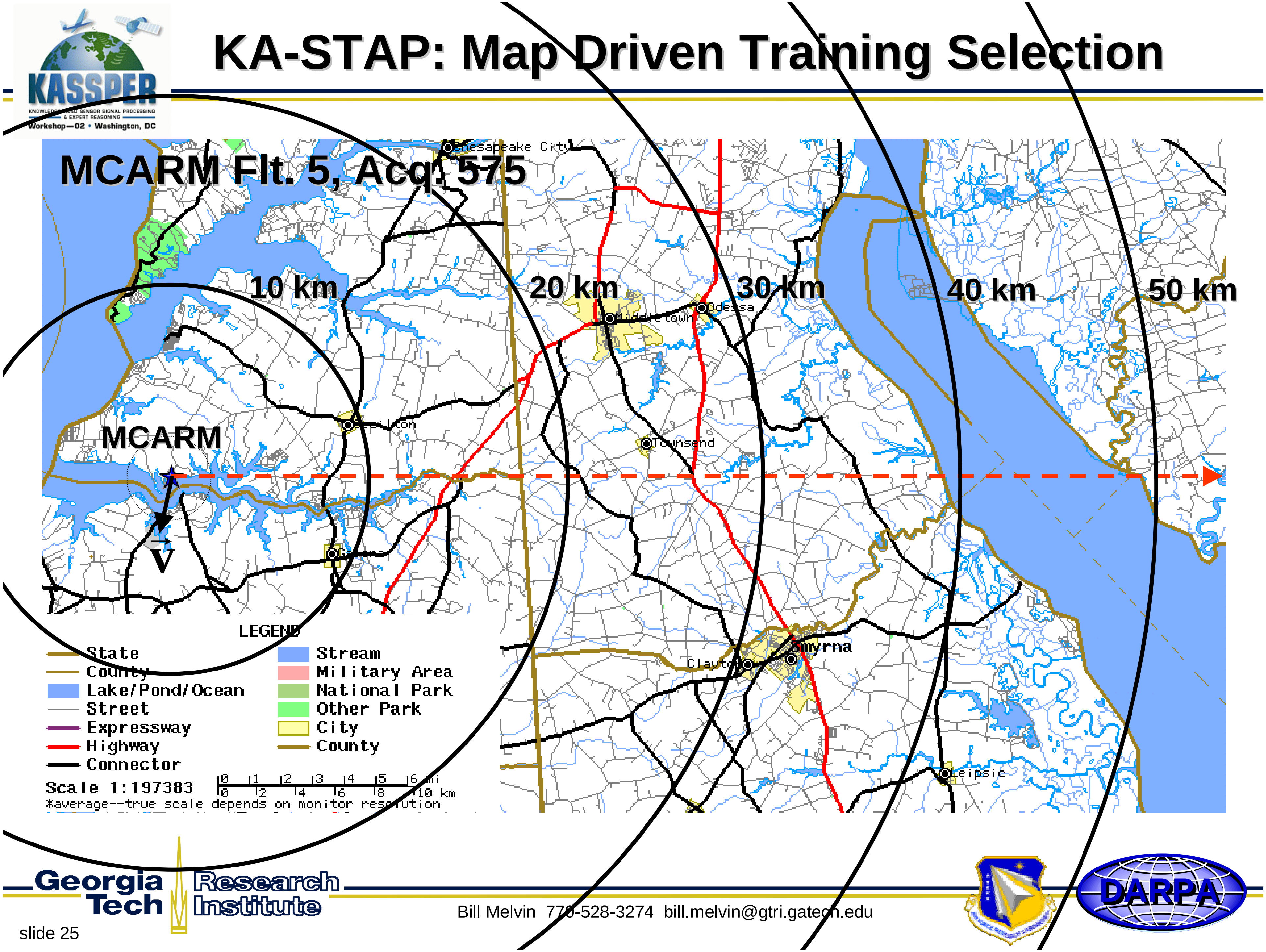
KA-STAP: Map Driven Training Selection



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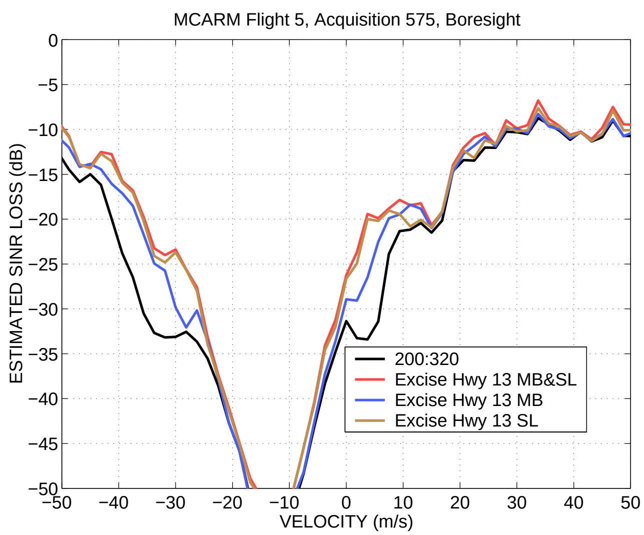
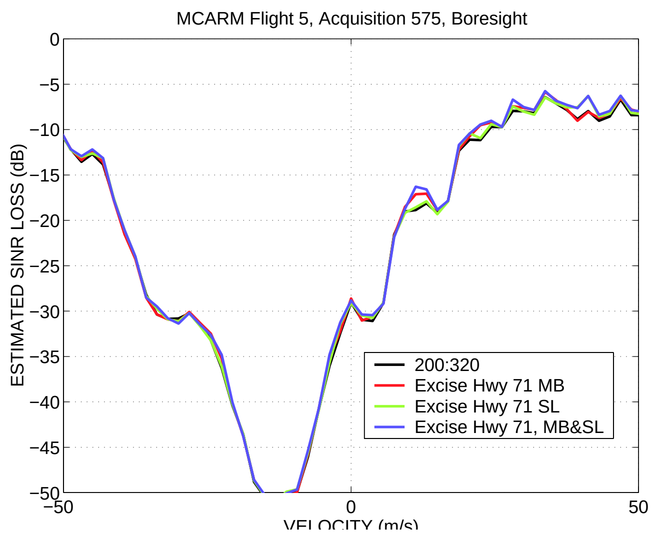
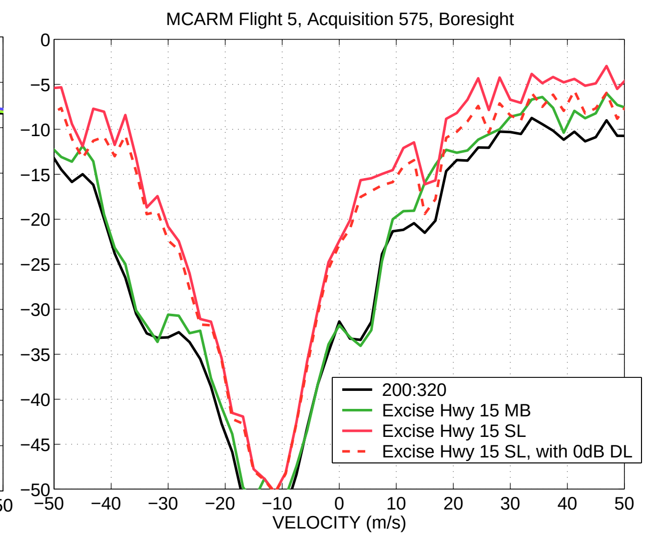
MCARM Flt. 5, Acquisition 575

Characterizing the Problem of TSD

Excising Hwy 13 in sidelobe (SL) region yields best results	No improvement when removing Hwy 71	Excising Hwy 15 in sidelobe region greatly improves performance







Comments

- Removing ranges with no target-like signals may emphasize TSD contributions from other cells
- Platform velocity and road geometry knowledge can be used to vary map-selected data by Doppler filter
- Processor can select range cell using map data and then "test" for TSD to either accept or reject

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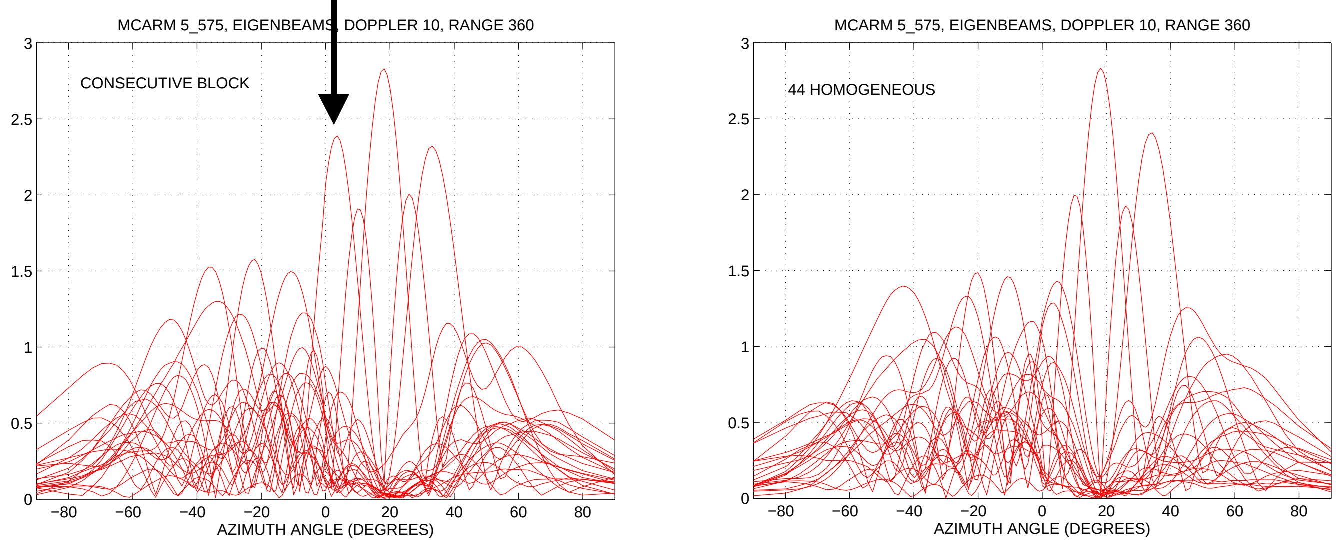
KA-STAP: Application of INU/GPS

- Angle-Doppler properties are known given platform velocity
- Eigen-discrimination can identify components off clutter ridge
- Pre-filtering can reduce required DoFs
  - MCARM vs. simulation (See slide 15)

Added component
due to movers



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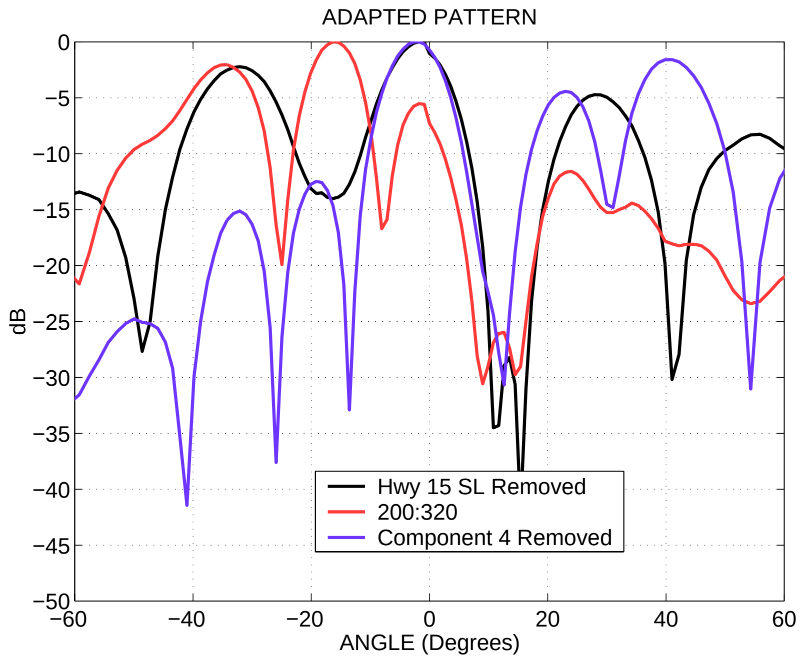
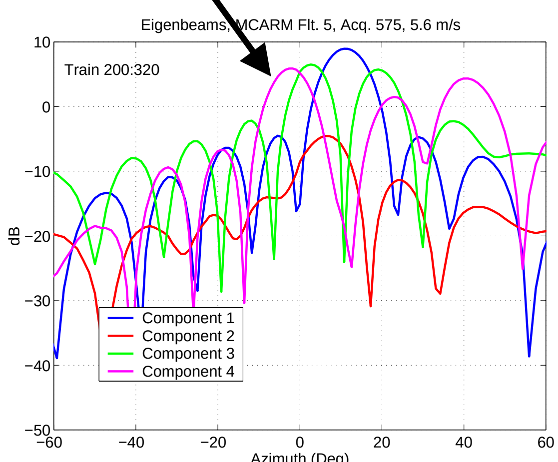
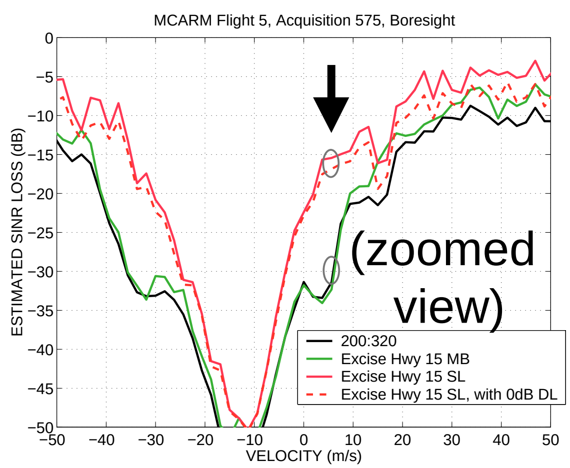
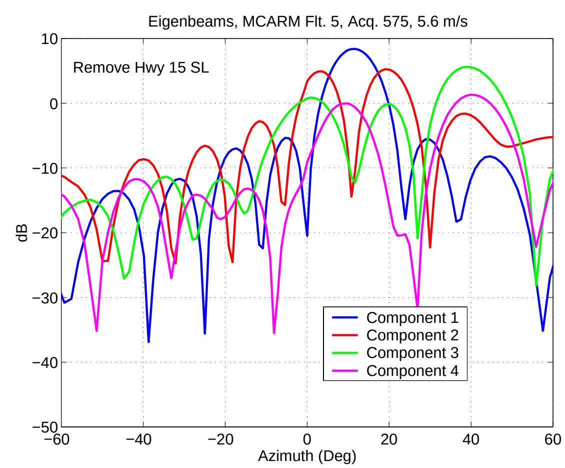
Eigen-Discrimination to Enhance Endo-Clutter Detection Performance



Component 4







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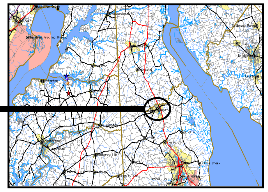
KA-STAP: Pre-Nulling Strategies

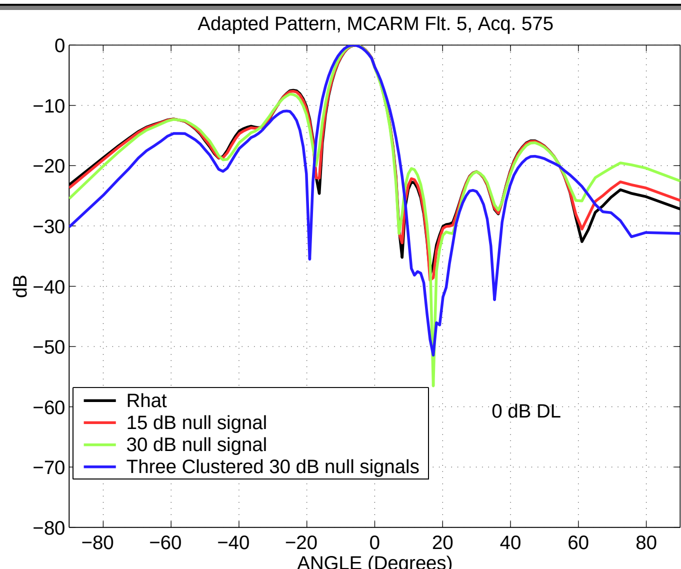


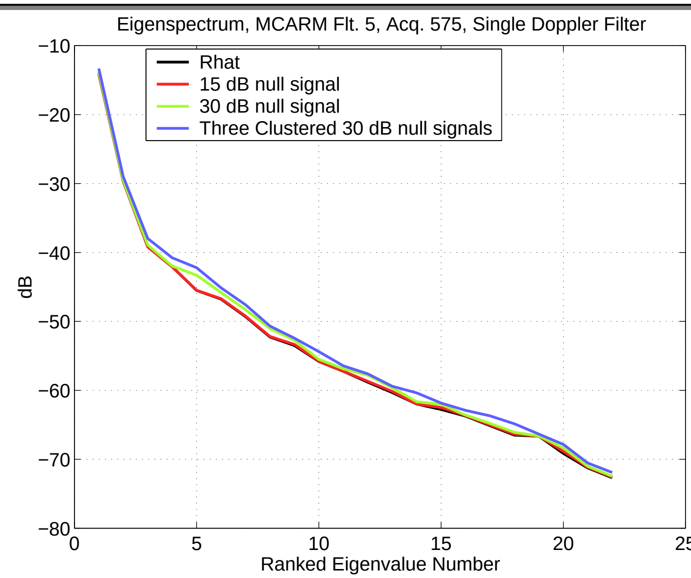
Map

INU/GPS

$$\hat{\mathbf{R}}_{\mathbf{k}} = \hat{\mathbf{R}}_{\mathbf{k/KA\text{-}Train}} \odot \mathbf{C}_{\mathbf{s\text{-}t/CMT}} + \hat{\mathbf{R}}_{\mathbf{k/Pre\text{-}Null}} + \sigma_{DL}^{2}\mathbf{I}_{\mathbf{NM}}$$

$$\hat{\mathbf{R}}_{\mathbf{k/Pre\text{-}Null}} = \sum_{p=1}^{N_{dir}} \left(\left(\mathbf{s}_{\mathbf{t}}(f_{d/p}(\gamma_p)) \mathbf{s}_{\mathbf{t}}^{H}(f_{d/p}(\gamma_p)) \right) \odot \mathbf{C}_{\mathbf{t/CMT}} \right) \otimes \left(\left(\mathbf{s}_{\mathbf{s}}(\gamma_p) \mathbf{s}_{\mathbf{s}}^{H}(\gamma_p) \right) \odot \mathbf{C}_{\mathbf{s/CMT}} \right)$$





Null Discrete Location (Smyrna)

Implementation Issues

- KASSPER implementations will likely require…
  - Case-based reasoning techniques
  - Map registration methods
- Case-based reasoning
  - Environmental assessment
  - Rank ordering of hypothesized effects
  - Sequential or parallel execution of a rationale KASSPER implementation
- Map registration issues [12]
  - Coarse requirements
    - Training data selection
    - Some KASSPER "triggers"
  - Finer alignment
    - High fidelity pre-filters

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Case-Based Reasoning (KA Control)

```
Switch Env
    Case A
        Switch Query 1
            Case A
                xxxxx
            Case B
                xxxx
            Otherwise
                xxxx
        End
        Switch Query 2
            Case A
                xxxx
            Case B
                xxxx
            Otherwise
                xxxx
        End
    Case B
        Etc.
    Case A U B
        Etc.
```

Determine the environment (apply database)

Query data/knowledge source 1, implement algorithm feature 1 (E.g., select DoF or match dominant subspace using database and deterministic prediction)

Query data/knowledge source 2, implement algorithm feature 2

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We're talking about….

5 to 15 dB!

potential for performance enhancement in realistic clutter environments

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Summary

- STAP is the data domain implementation of an optimal filter
  - Homogeneous training data required to construct STAP
    - Homogeneous = independent and identically distributed (iid)
- Real-world environments tend to appear heterogeneous
- Via simulation and actual measured data, we have overviewed the impact of clutter heterogeneity on STAP performance
- Several knowledge-assisted (KA) mitigating strategies were suggested

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