

Development and Implementation of a Knowledge Aided STAP Algorithm

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The logo for Information Systems Laboratories, Inc. (ISL) features the letters 'ISL' in a large, bold, blue, stylized font. The 'I' and 'S' are connected, and the 'L' is a simple vertical bar. The text 'INFORMATION SYSTEMS LABORATORIES, INC.' is positioned to the left of the logo in a smaller, blue, sans-serif font.

Outline

- **Background**
- **Knowledge-Aided Data Pre-Whitening**
- **Example Applications**
 - Distributed clutter
 - Discrete clutter
 - Combined discrete and distributed clutter
- **Real-Time Implementation Analysis**
 - Implementation approach
 - Real-time demonstration status
- **Future Plans and Summary**

Background

- **Clutter cancellation based on *a priori* knowledge alone will often not result in adequate performance**
- **Focus will be on techniques that combine or “blend” adaptive and deterministic filtering**
- **The desired approach is to cancel the known interference component (data pre-conditioning) → follow up with adaptive processing → will require fewer DoFs**
- **Improves performance in heterogeneous clutter environments**
 - Localized training to better “match” the clutter notch width
 - Overcome limited sample support caused by editing techniques
- **Looking for techniques with these properties:**
 - Combines deterministic (knowledge-aided) and adaptive filtering in a way that reduces the overall number of training samples
 - Can be implemented/integrated into existing data domain STAP processing architectures

Interference Modeling

- Assume the clutter signal plus thermal noise model

$$\mathbf{x} = \mathbf{x}_c \circ \mathbf{t} + \mathbf{n} \quad \circ - \text{Hadamard element-wise product}$$

- The modulation is typically small

$$\mathbf{t} = \mathbf{1} + \mathbf{d} \quad \mathbf{d} \text{ is zero-mean, variance } \ll 1$$

- Clutter signal with small modulation

$$\mathbf{x} = \mathbf{x}_c + \mathbf{x}_c \circ \mathbf{d} + \mathbf{n}$$

- Clutter correlation matrix

$$E\{\mathbf{x}\mathbf{x}^H\} = \mathbf{R}_{\mathbf{xx}} = E\{\mathbf{x}_c\mathbf{x}_c^H\} + E\{\mathbf{x}_c\mathbf{x}_c^H\} \circ E\{\mathbf{d}\mathbf{d}^H\} + \sigma^2\mathbf{I}$$

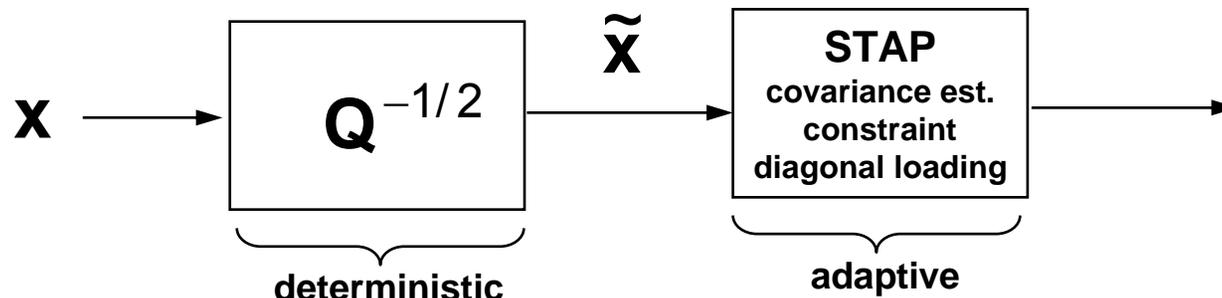
$$= \mathbf{R}_c + \underbrace{\mathbf{R}_c \circ \mathbf{T}}_{\text{unknown component}} + \sigma^2\mathbf{I}$$

“known” component →

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KA Signal Processing Approach



- **The desired approach is to cancel the known interference component (data pre-conditioning)**
 - Full ground clutter model
 - Discretized
 - Jammers/RFI
- **Follow up with adaptive processing → will require fewer DoFs**
- **This two-stage form does not readily “fit” existing data domain STAP implementations**

Knowledge-Aided Quadratic Constraints

Reduced-DoF STAP

- We can incorporate the reduced-DoF covariance model as a quadratic constraint

$$\min_{\mathbf{w}_m} E\{|\mathbf{w}_m^H \mathbf{x}_m|^2\} \quad \text{s.t.} \quad \begin{cases} \mathbf{w}_m^H \mathbf{v}_m = 1 \\ \mathbf{w}_m^H \mathbf{R}_{c,m} \mathbf{w}_m \leq \delta_{d,m} \\ \mathbf{w}_m^H \mathbf{w}_m \leq \delta_{L,m} \end{cases}$$

want weights to be “orthogonal” to the reduced-DoF *a priori* clutter model

this is the KA part

- Gives:

$$\mathbf{w}_m = \frac{(\mathbf{R}_m + \beta_{d,m} \mathbf{R}_{c,m} + \beta_{L,m} \mathbf{I})^{-1} \mathbf{v}_m}{\mathbf{v}_m^H (\mathbf{R}_m + \beta_{d,m} \mathbf{R}_{c,m} + \beta_{L,m} \mathbf{I})^{-1} \mathbf{v}_m} = \frac{(\mathbf{R}_m + \mathbf{Q}_m)^{-1} \mathbf{v}_m}{\mathbf{v}_m^H (\mathbf{R}_m + \mathbf{Q}_m)^{-1} \mathbf{v}_m}$$

“colored loading” 

- Same form as full-DoF case
- Can be readily implemented in the data domain
- Can also be shown to be a prefilter on the reduced DoF data (next slide)

Pre-Filter Interpretation

- Colored loading beamformer can be expressed as:

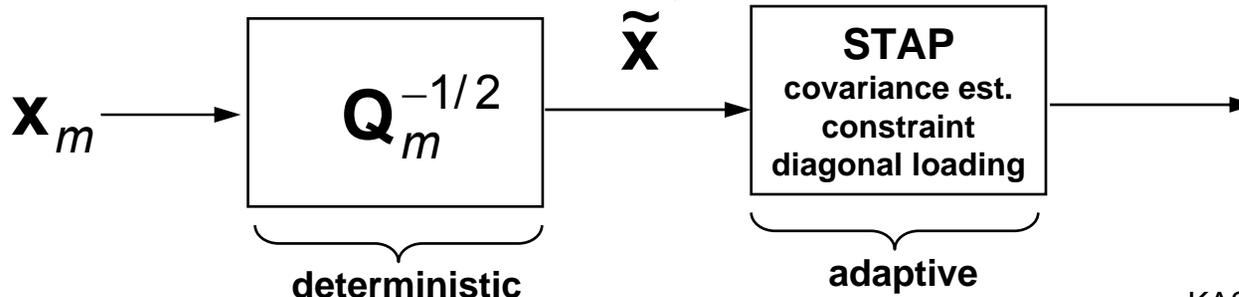
$$\mathbf{W} = \frac{\mathbf{Q}_m^{-1/2} (\mathbf{Q}_m^{-1/2} \mathbf{R}_m \mathbf{Q}_m^{-1/2} + \mathbf{I})^{-1} \mathbf{Q}_m^{-1/2} \mathbf{v}_m}{\mathbf{v}_m^H \mathbf{Q}_m^{-1/2} (\mathbf{Q}_m^{-1/2} \mathbf{R}_m \mathbf{Q}_m^{-1/2} + \mathbf{I})^{-1} \mathbf{Q}_m^{-1/2} \mathbf{v}_m}$$

- This filtering solution is equivalent to *deterministic* pre-filtering followed by *adaptive* processing (i.e., 2 stages)

$$\tilde{\mathbf{x}} = \mathbf{Q}_m^{-1/2} \mathbf{x}_m \quad \tilde{\mathbf{v}} = \mathbf{Q}_m^{1/2} \mathbf{v}_m$$

$$\tilde{\mathbf{W}} = \frac{(\mathbf{R}_{\tilde{\mathbf{x}}\tilde{\mathbf{x}}} + \mathbf{I})^{-1} \tilde{\mathbf{v}}}{\tilde{\mathbf{v}}^H (\mathbf{R}_{\tilde{\mathbf{x}}\tilde{\mathbf{x}}} + \mathbf{I})^{-1} \tilde{\mathbf{v}}}$$

it will generally be easier to estimate the interference covariance of the pre-filtered data than the original data because it is likely to have a lower effective rank



Constraint Satisfaction

- The two loading levels are determined by assuring satisfaction of the two soft constraints
- Leads to two coupled non-linear inequality relations for the two real scalar loading levels embedded in \mathbf{Q}

$$\mathbf{v}^H (\mathbf{R}_{xx} + \mathbf{Q})^{-1} \mathbf{R}_c (\mathbf{R}_{xx} + \mathbf{Q})^{-1} \mathbf{v} \leq \delta_d \left(\mathbf{v}^H (\mathbf{R}_{xx} + \mathbf{Q})^{-1} \mathbf{v} \right)^2 \quad (1)$$

$$\mathbf{v}^H (\mathbf{R}_{xx} + \mathbf{Q})^{-2} \mathbf{v} \leq \delta_L \left(\mathbf{v}^H (\mathbf{R}_{xx} + \mathbf{Q})^{-1} \mathbf{v} \right)^2 \quad (2)$$

- No closed form solution, must be solved iteratively
- In the white noise gain relation, $\delta_L > 0$ to obtain solution
- In the clutter orthogonality relation, reducing δ_d requires that the colored loading level β_d be increased
- In the limit of $\delta_d \rightarrow 0$ (true orthogonality of weights to the clutter model), $\beta_d \rightarrow \infty$
- This can be demonstrated directly by comparing the quadratic constraint weight solution with a multiple linear constraint weight solution that enforces orthogonality explicitly

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Distributed Clutter Colored Loading

- The ground clutter covariance model is given as

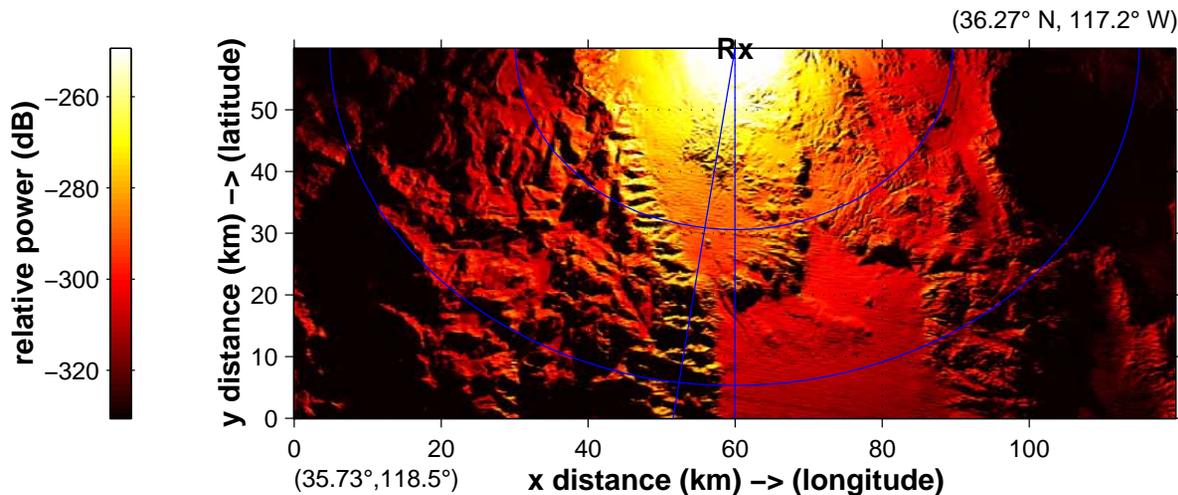
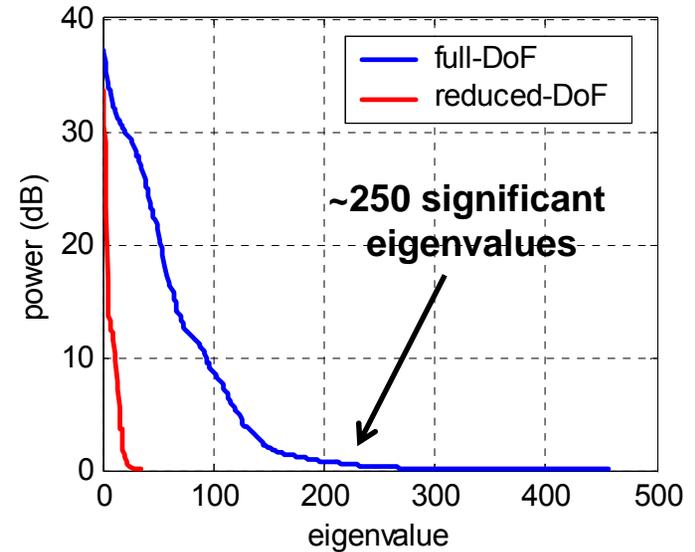
$$\mathbf{R}_c = \sum_{p=1}^{N_c} |\alpha_p|^2 \mathbf{v}(\theta_p, f_p) \mathbf{v}(\theta_p, f_p)^H \quad \mathbf{R}_{c,m} = \mathbf{H}_m^H \mathbf{R}_c \mathbf{H}_m$$

- Where α_p may include assumed Tx and Rx subarray patterns and the ground clutter power based on a site-specific terrain model (e.g. DTED)
- Unknown quantities in the covariance model analyzed:
 - Angle independent calibration errors (gain and phase)
 - Angle dependent calibration errors
 - ICM
 - Terrain ($\alpha_p = 1$)
 - transmit pattern
- The knowledge-aided STAP weights are computed as

$$\mathbf{w}_m = \kappa (\mathbf{R}_{s,m} + \beta_{L,m} \mathbf{I} + \beta_{d,m} \mathbf{R}_{c,m})^{-1} \mathbf{v}_m$$

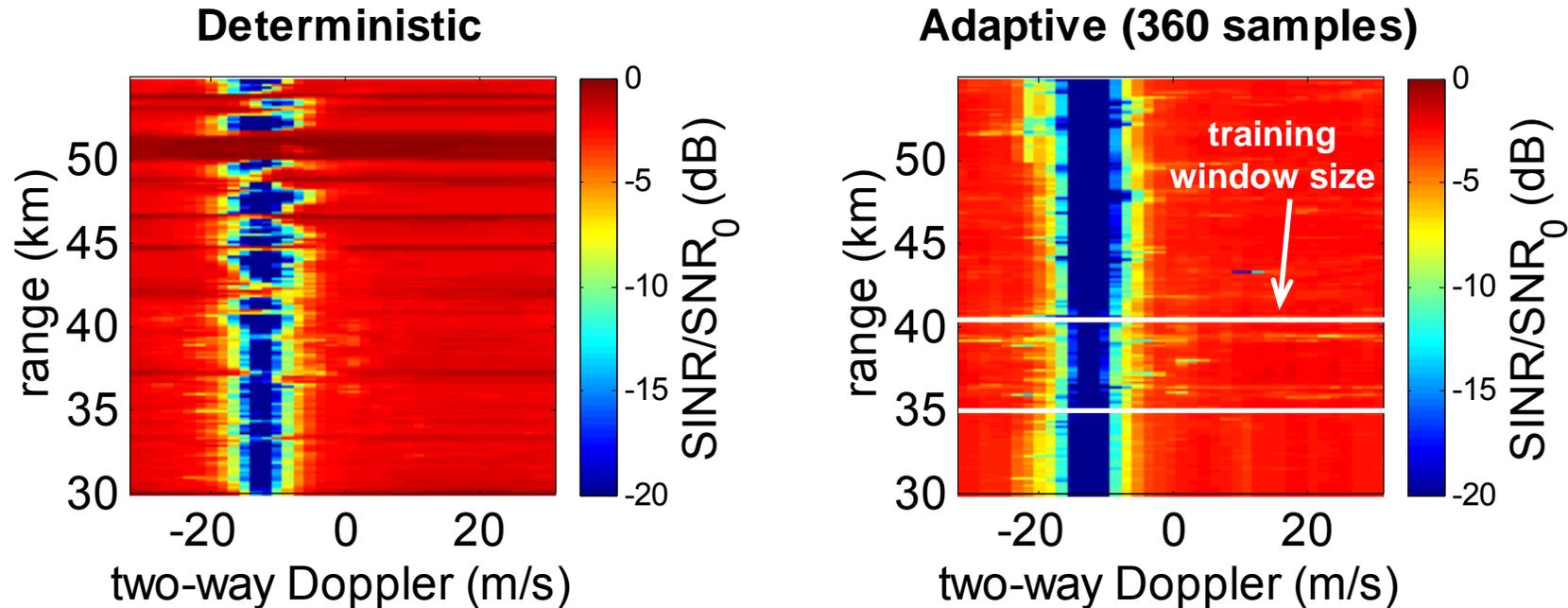
KASSPER Data Set 2

Parmeter	Value
RF frequency	10000 MHz
Bandwidth	10 MHz
PRF	2000 Hz
Peak Power	10 kW
Duty factor	10%
Noise figure	5 dB
System losses	7 dB
Platform speed	150 m/s
Platform altitude	7 km ASL
Receive aperture	1.425 m x 0.285 m
Number of subarrays	12
crab	~3 degrees
Number of Pulses	38



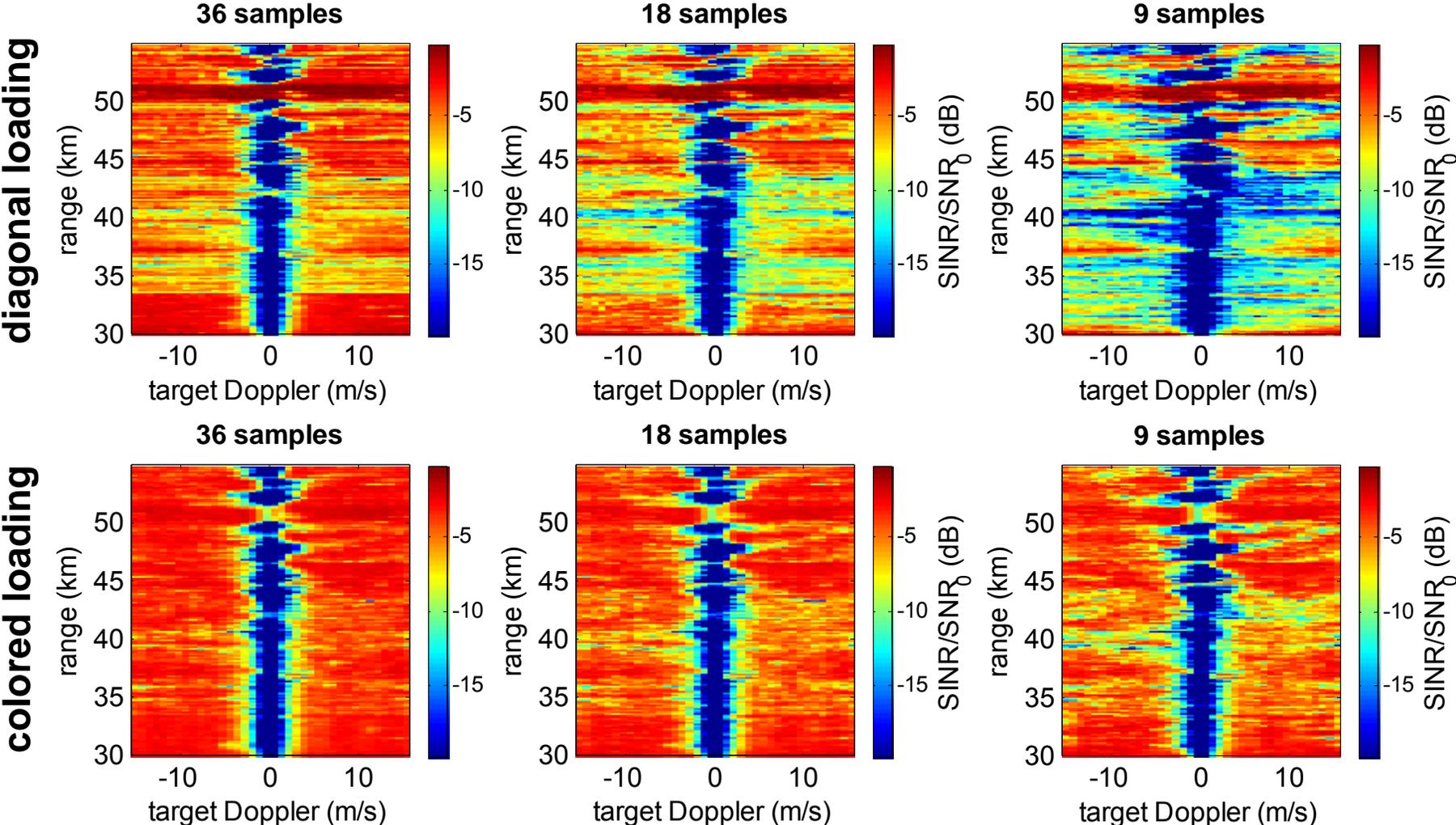
- Site-specific data set generated under KASSPER program
- Heterogeneous clutter, ground vehicles, ICM, calibration errors
- Eigenvalues shown for range bin 100

Traditional STAP



- Comparison of ideal covariance SINR loss (left) and “traditional” STAP SINR loss (right)
- STAP results in wider clutter notch → poorer MDV if training window is wide compared to clutter “features”

KASSPER Data Set 2

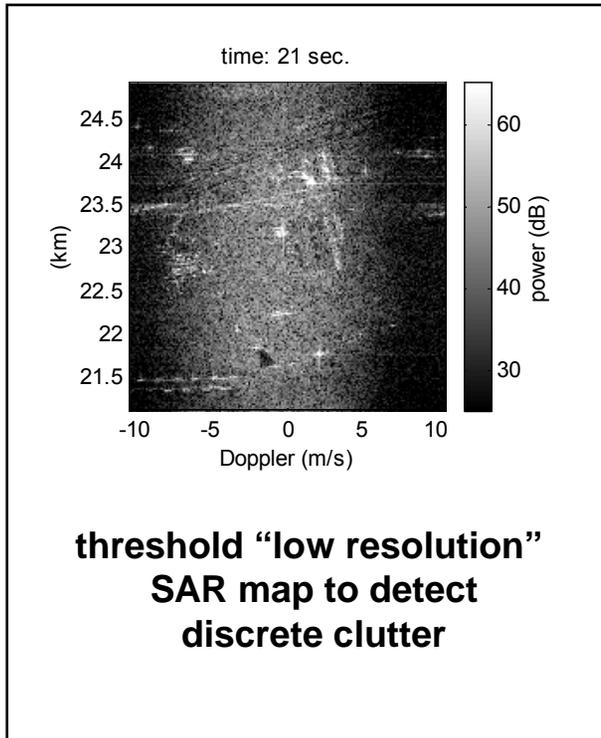


Outline

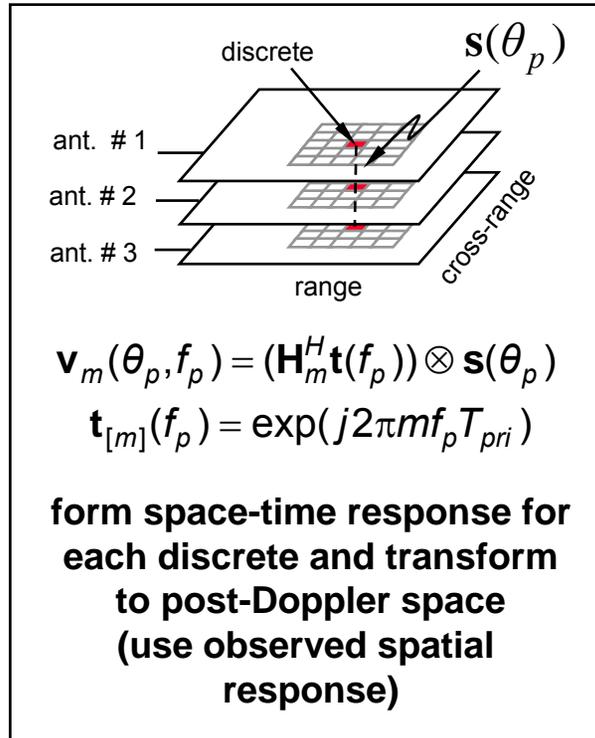
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Discrete Clutter Colored Loading

STEP 1



STEP 2



STEP 3

$$\mathbf{Q}_{m,l} = \sum_{p=1}^{P_c} \mathbf{v}_{m,l}(\theta_p, f_p) \mathbf{v}_{m,l}^H(\theta_p, f_p)$$

$$\mathbf{R}_{m,l} = \frac{1}{K} \sum_{k=1}^K \mathbf{x}_{m,k} \mathbf{x}_{m,k}^H + \beta \mathbf{Q}_{m,l} + \mathbf{I}$$

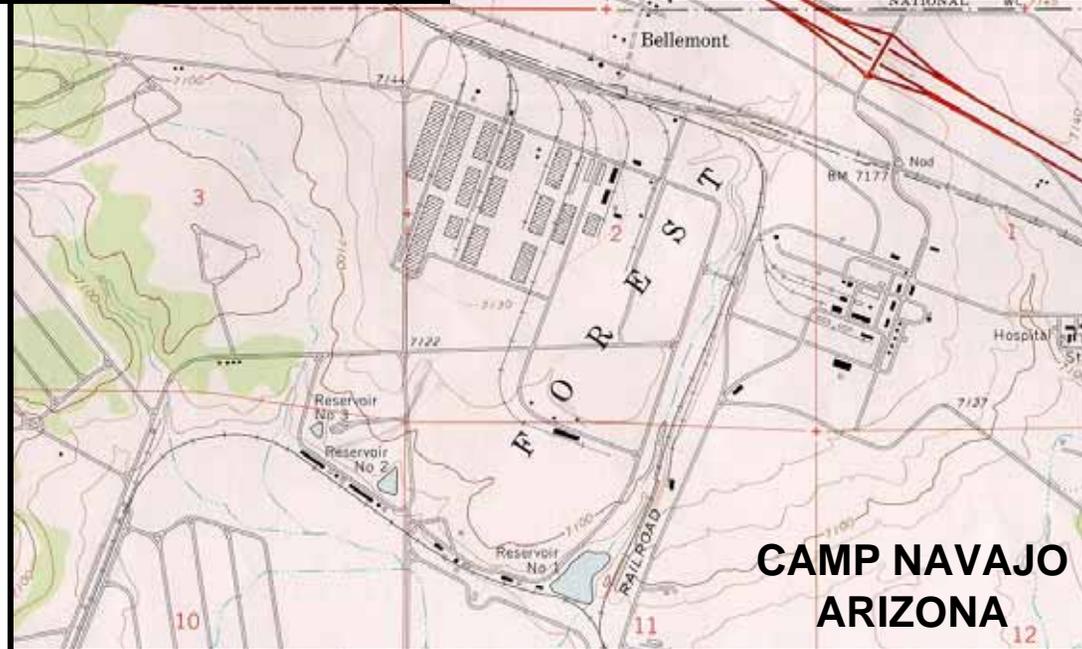
use responses to form a range-dependent “loading” matrix for each Doppler bin, add to sample cov. and run STAP processor

- 0.5 second CPI used to form “low resolution” SAR for discrete detector
- Final STAP processing w/ colored loading is performed on 100 ms CPI
- Discrete amplitudes not used in current implementation
- Colored loading level set to ~20 dB re. thermal noise
- Diagonal loading level set to ~0 dB re. thermal noise



Tuxedo Data

Recorded Data



System Parameters for GMTI Mode

Center Freq.	9.6 GHz
Bandwidth	66 MHz
PRF	1,383 Hz
Tx Apertures	1
Rx Apertures	3
Az BW, Aperture	3.6 deg
EI BW, Aperture	9.1 deg
Polarization	HH
A/C Heading	290 deg
Depr. Angle	15 deg
Recorded Time	30 sec

Post-Doppler, PRI-
Staggered STAP:
Staggers 2
Stagger Offset 3 Pulses
CPI: 100 ms (128 pulses)

Limited targets in data (up to 5) and uniform terrain type (desert)

Baseline Processing

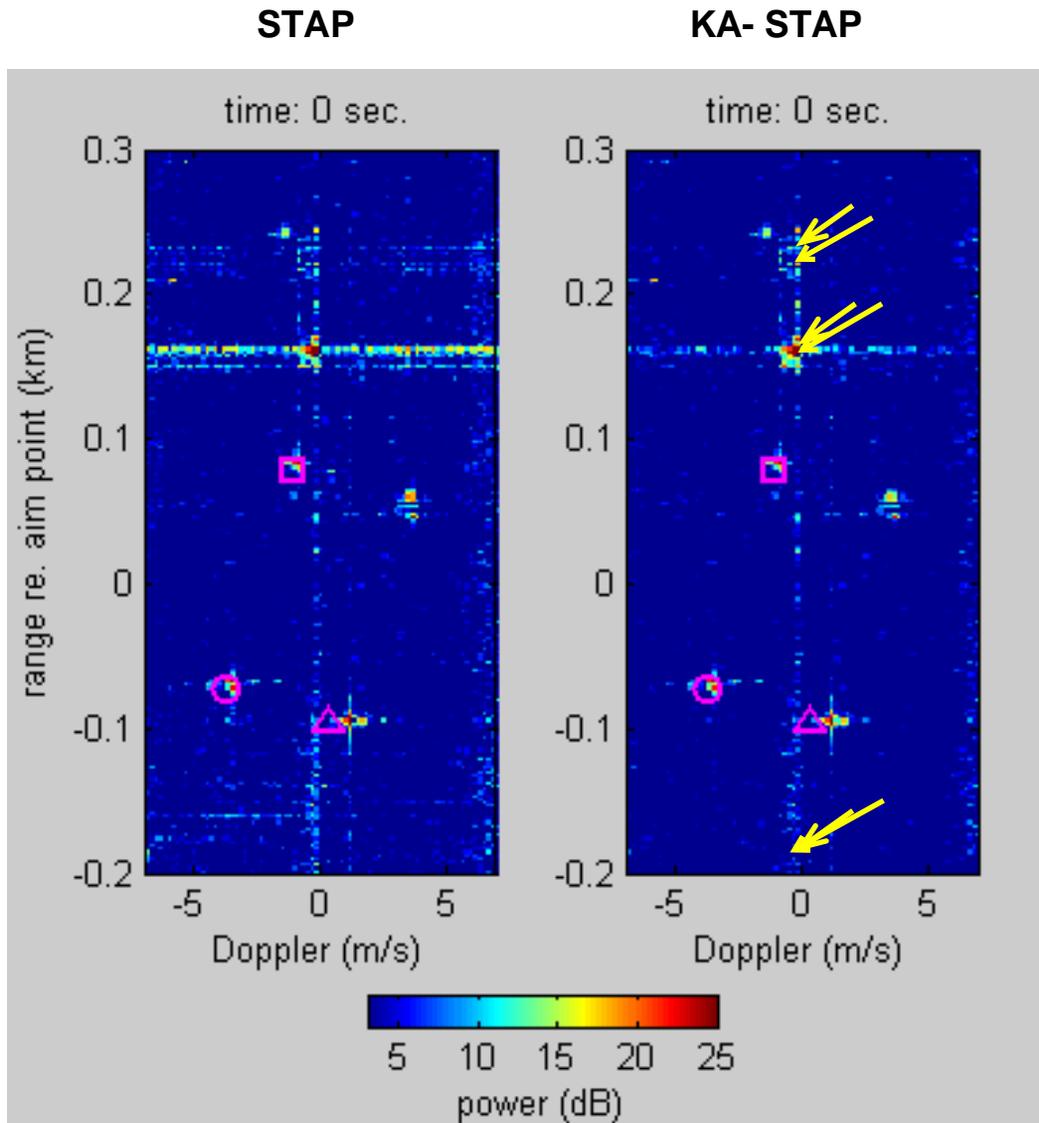
Conventional

STAP



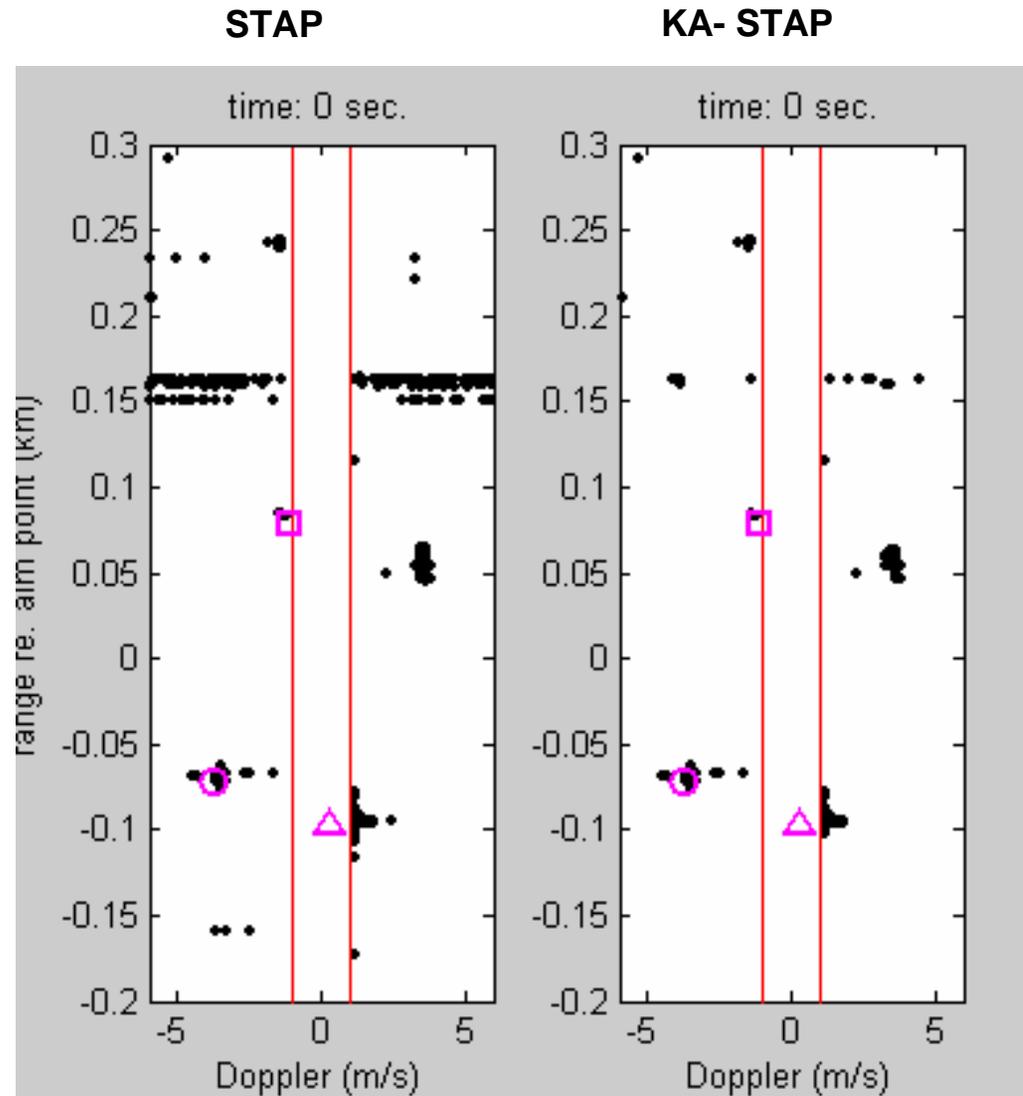
- **STAP**
 - 3 bin post-Doppler
 - element space
 - 200 training bins
 - 3 guard bins on each side
 - diagonal loading
- **Three truth targets provided with data**
 - circle: HMMWV
 - square: fuel truck
 - triangle: 5-ton truck
- **Additional targets observed**
- **Significant under-nulled clutter observed due to discretizes**

KA-STAP Processing



- STAP parameters same as previous slide
- KA-STAP also uses 200 training samples →
- Discrete threshold is ~30 dB re. thermal noise
- Discretions limited to region around zero Doppler (-0.5 m/s to +0.5 m/s)
- KA technique results in significant reduction of under-nulled clutter
- KA-STAP does not appear to impact moving target responses (i.e., pd is maintained)
- Yellow arrows mark locations of observed large clutter discretions

Raw Detections



- **STAP weights normalized to give unit gain on thermal noise**
- **Constant threshold set at 10 re. thermal noise (no CACFAR)**
- **Detections for 3 CPIS shown in each movie frame**
- **No detections recorded between -1 m/s and 1 m/s**
- **KA technique results in fewer false alarms due to under-nulled clutter**
- **KA-STAP does not impact moving target responses (i.e., pd is maintained)**

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Composite Colored Loading

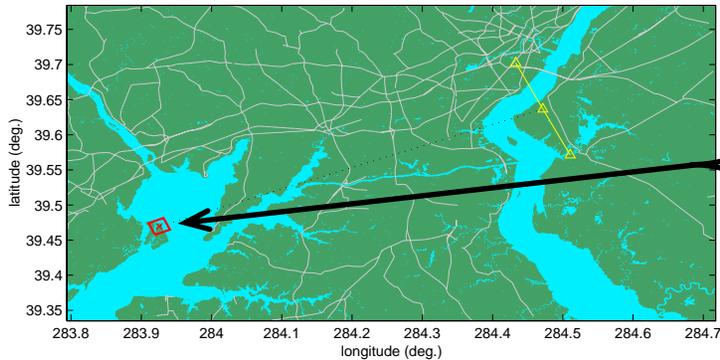
- Colored loading can be readily applied to simultaneously address contributions due to distributed and discrete clutter
→ add two loading matrices

$$\mathbf{w}_m = \kappa(\mathbf{R}_{s,m} + \beta_{L,m}\mathbf{I} + \beta_{d_1,m}\mathbf{R}_{c_1,m}^1 + \beta_{d_2,m}\mathbf{R}_{c_2,m})^{-1}\mathbf{v}_m$$

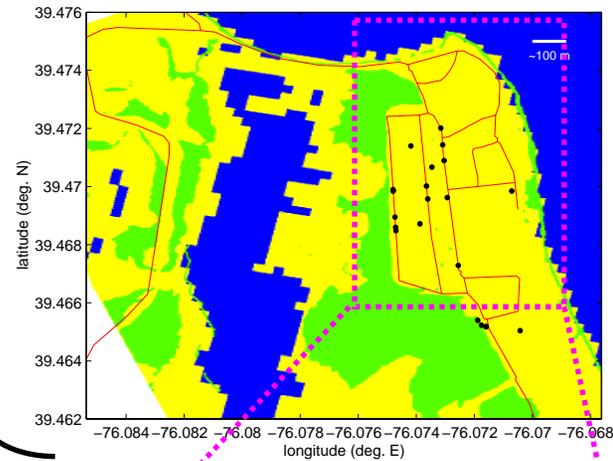
distributed clutter discrete clutter

- Discrete clutter component is generally range dependent → will require updating the weights for each discrete to be nulled

KASSPER Data Set 3 Overview



land cover, roads, targets



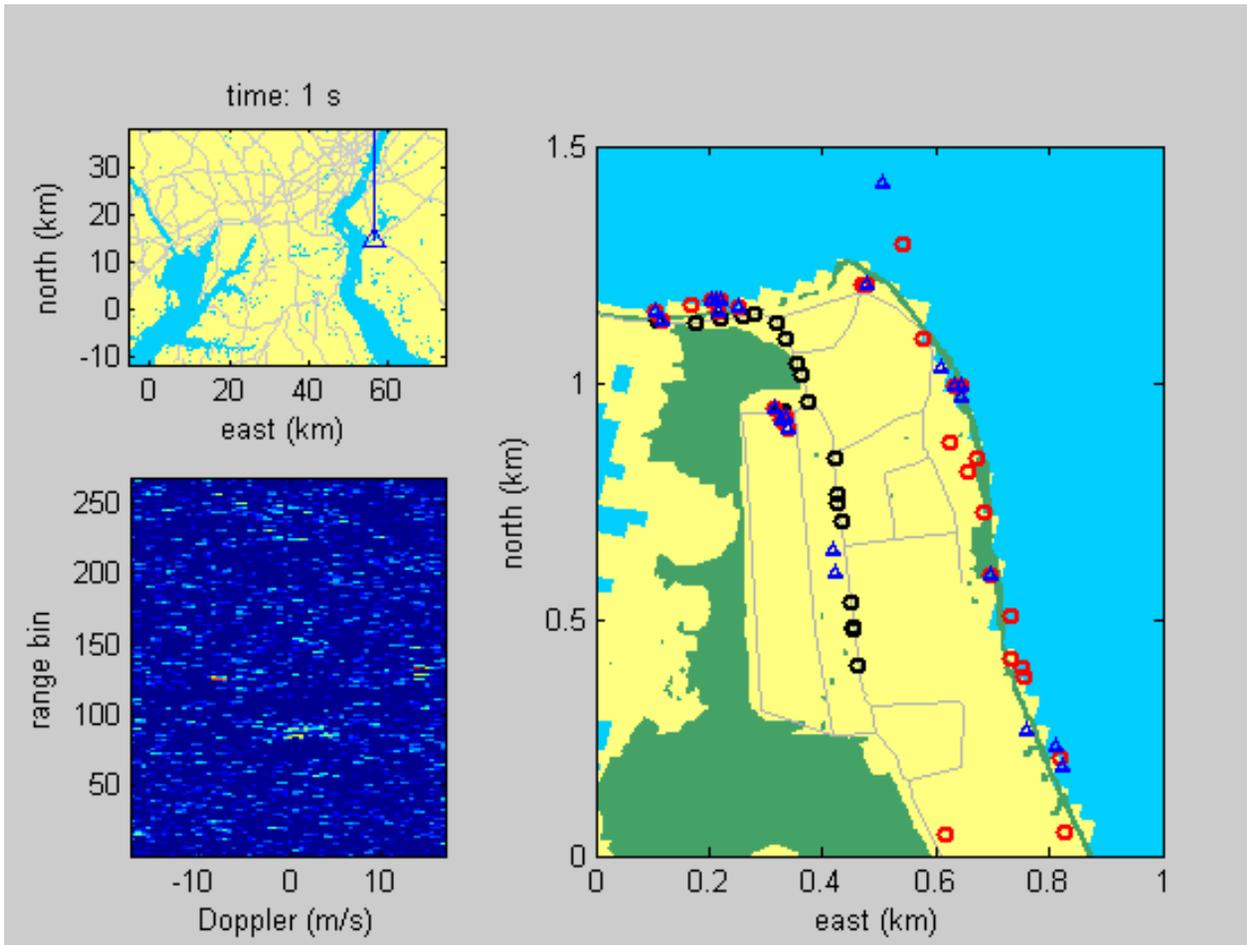
Freq.	X-band
BW	20 MHz
PRF	1 kHz
Pulses	64
Ant.	3.5 m x 0.3 m
ICM	Billingsley (15 m.p.h.)

- 30 CPIs spanning 2.5 minutes (5 sec. revisit)
- Ground clutter characterized by geo-coded SAR images provided by ALPHATECH
- USGS land cover used for ICM
- 22 slow-moving ground targets traveling on and off roads

SAR image w/ roads



KASSPER Data Set 3

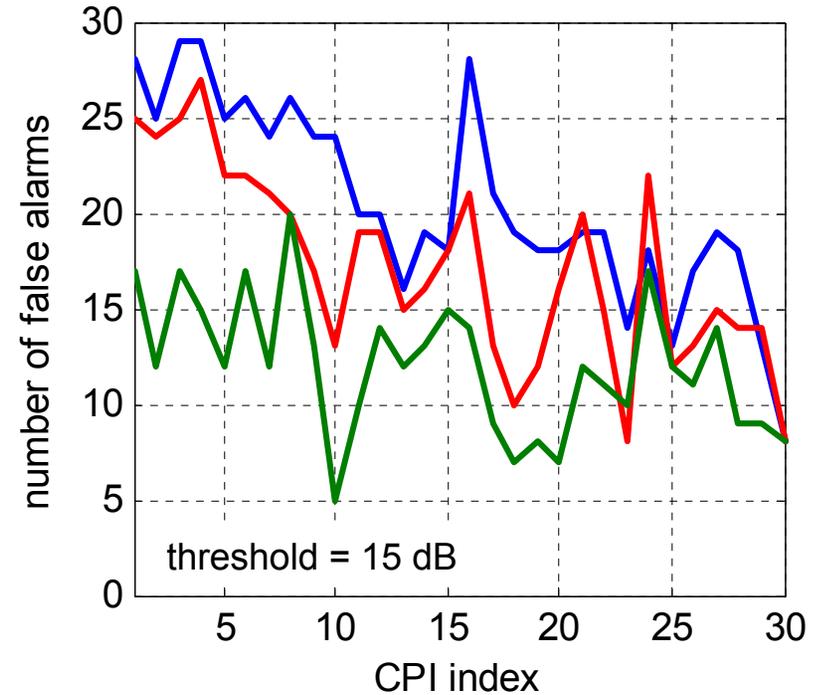
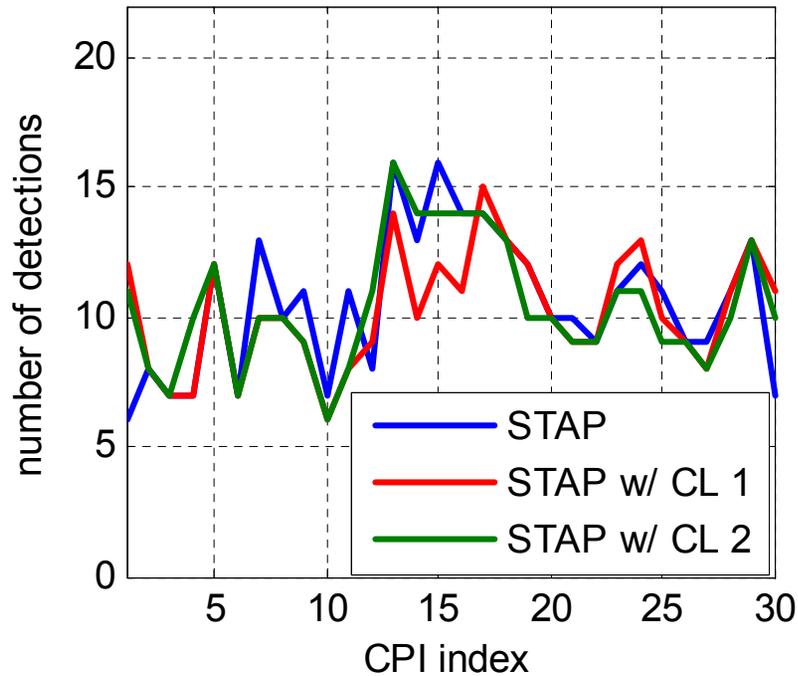


- Upper left: wide-area view with platform and scanning angle
- Lower left: range-Doppler beamformer output after CFAR normalization
- Right: plan view with land cover, truth and detections
 - Land cover
 - » Blue: water
 - » Green: trees
 - » Yellow: grass
 - » Gray lines: roads
 - black: truth
 - blue: STAP w/ CL
 - red: STAP

NOTES:

- 3 bin post-Doppler element space STAP
- 36 training samples – excluding bin under test
- Clutter-only data used for training (i.e., no target contamination)
- Full-DoF colored loading level set to 20 dB re. noise
- Diagonal loading set to 3 dB re. noise
- 15 dB threshold re. noise

Detection Summary



- Truth target declared detected when there is at least one detection that associates (22 total truth targets)
- Detections that do not associate with a truth target are considered false alarms
- Results shown for distributed clutter colored loading ('STAP w/ CL 1') and composite colored loading ('STAP w/ CL 2')
- The 10 largest discretized in the conventional beamformer range-Doppler clutter map are used in the composite CL model

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Data Domain STAP

- Problem is to solve linear system of equations to get the weight vector:

$$\mathbf{w} = \mathbf{R}_s^{-1} \mathbf{s} \leftrightarrow \mathbf{R}_s \mathbf{w} = \mathbf{s}$$

- Since the sample covariance is typically Hermitian and positive definite one approach is to find its Cholesky decomposition

$$\mathbf{C}^H \mathbf{C} \mathbf{w} = \mathbf{s}$$

- The matrix \mathbf{C} is upper triangular so the solution can be readily found using a forward and backward substitution

$$\mathbf{C}^H \mathbf{y} = \mathbf{s} \rightarrow \mathbf{C} \mathbf{w} = \mathbf{y}$$

Data Domain STAP (cont.)

- It turns out that \mathbf{C} can be found without forming the sample covariance by performing a QR decomposition (Q unitary, R upper triangular) on the data matrix directly

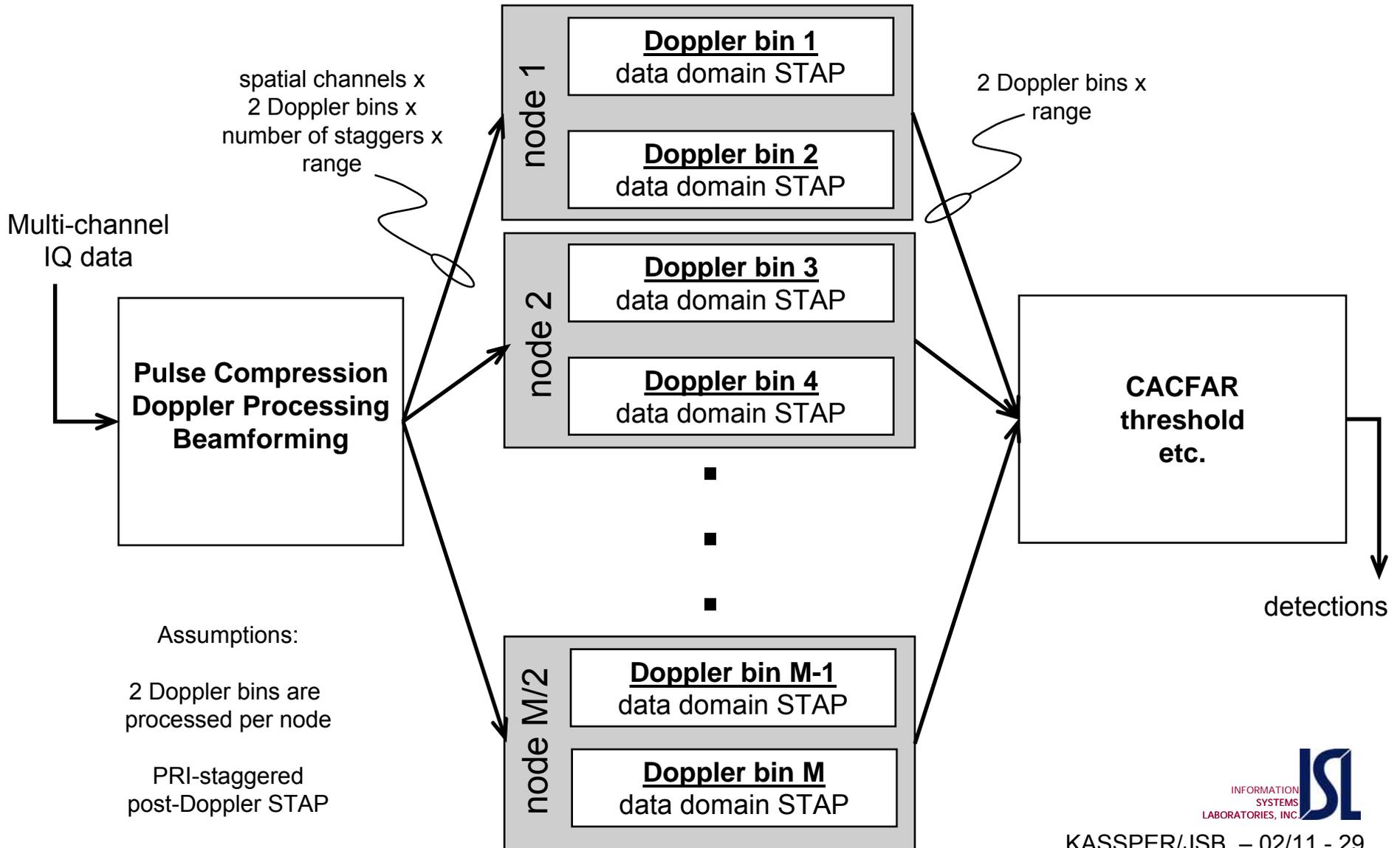
$$\mathbf{X}^H = \mathbf{Q}\mathbf{R} \Rightarrow \mathbf{R}_s = \mathbf{X}\mathbf{X}^H = (\mathbf{Q}\mathbf{R})^H(\mathbf{Q}\mathbf{R}) = \mathbf{R}^H\mathbf{R}$$

- In this case R is upper triangular and equivalent to the Cholesky decomposition of \mathbf{R}_s so it can readily be used to solve for the weight vector (see previous slide)
- It is possible to compute R without explicitly finding Q which saves significant computations
- Diagonal loading can be included by simply augmenting the data matrix

$$\mathbf{X}_a = \left[\mathbf{X} \quad \sqrt{\beta}\mathbf{I} \right] \Rightarrow \mathbf{R}_{s,L} = \mathbf{X}_a\mathbf{X}_a^H = \mathbf{R}_s + \beta\mathbf{I}$$

- In general any solution that adds a positive semi-definite matrix to the covariance can be implemented by an appropriate augmentation of the data matrix in the data domain implementation

STAP Algorithm Partitioning Example



Data Domain Colored Loading

- Typically, the loading matrix \mathbf{Q}_m is Hermitian and positive-definite so that its Cholesky decomposition exists

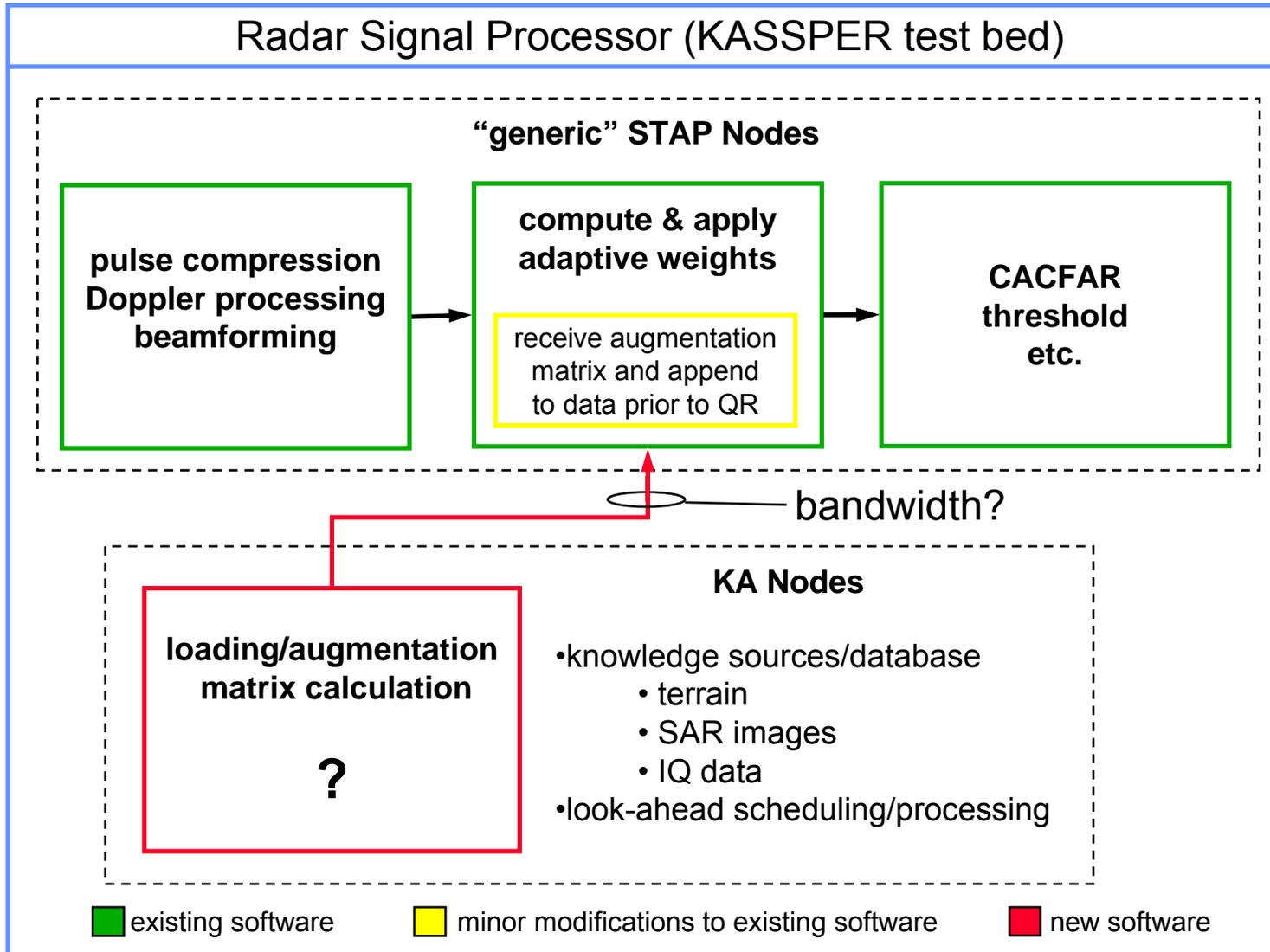
$$\mathbf{Q}_m = \beta_d \mathbf{R}_{c,m} + \beta_L \mathbf{I} = \mathbf{Q}_m^{1/2} \mathbf{Q}_m^{1/2} = \mathbf{C}_m^H \mathbf{C}_m \quad \mathbf{C}_m \text{ is upper triangular}$$

- Can be efficiently implemented in the data domain by augmenting data matrix and using QR decomposition

$$\mathbf{X}_a = [\mathbf{X}_m \quad \sqrt{K} \mathbf{C}^H] \rightarrow \frac{1}{K} \mathbf{X}_a \mathbf{X}_a^H = \mathbf{R}_s + \mathbf{Q}_m$$

- Thus, pre-filter approach implemented as colored loading actually “fits” existing STAP computing architectures (if they already employ data domain processing with diagonal loading)

Real-Time Implementation Approach



Bandwidth Requirements

- **Assumptions:**

- One complex $D \times D$ loading/augmentation matrix is required per Doppler bin per CPI
 - » In covariance domain matrix is Hermitian symmetric
 - » In data domain matrix is all zeros below main diagonal
 - » Only need to send upper (or lower) triangular part of the matrix
- 128 Doppler bins
- 100 ms CPI length
- 2 staggers, 3 beams ($D = 6$)
- Double precision real and imaginary data

- **Bandwidth required to communicate augmentation matrices**

$$BW = \frac{(128\text{bits})(128)(D(D + 1)/2)}{100\text{ms}} = 3.4\text{Mbps}$$

- **May want to only apply this technique to a small number of Doppler bins**

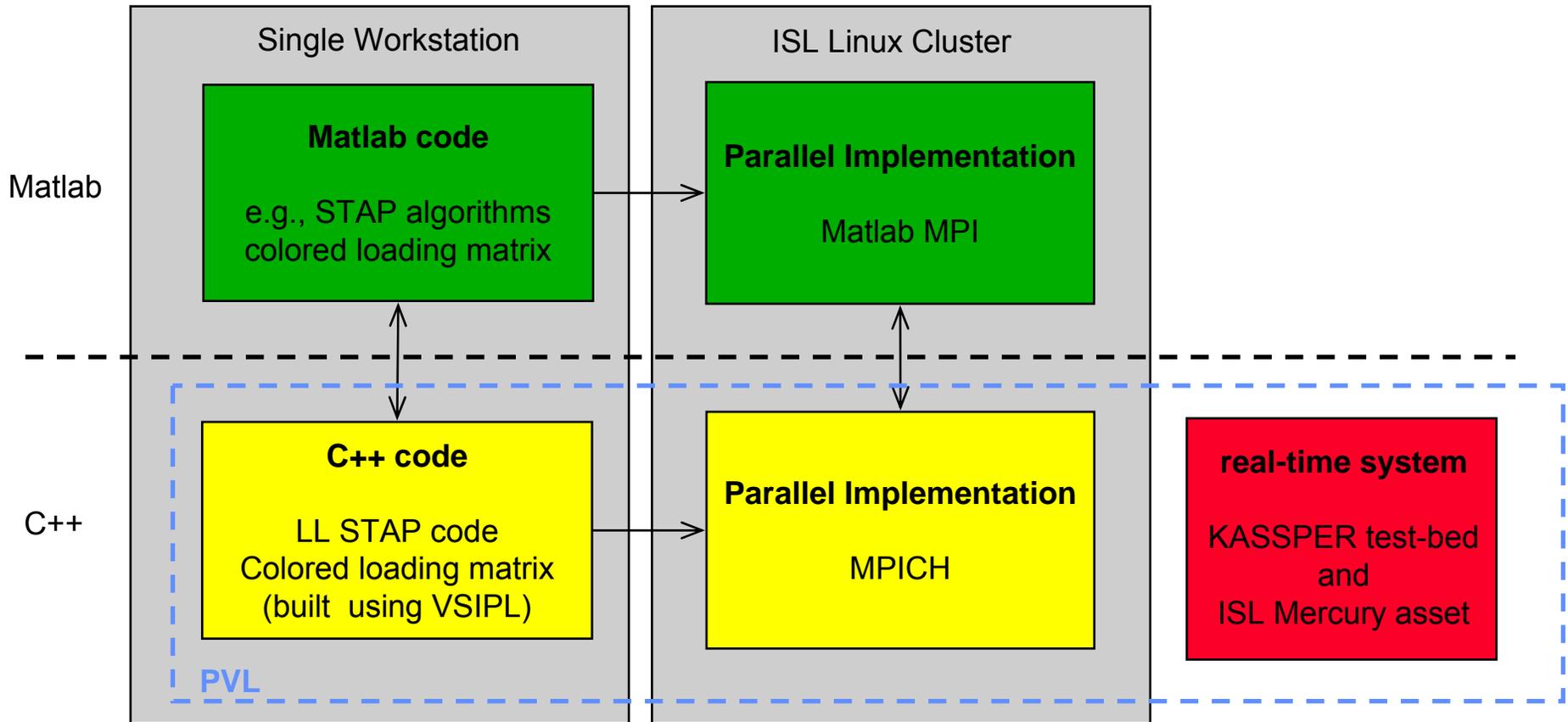
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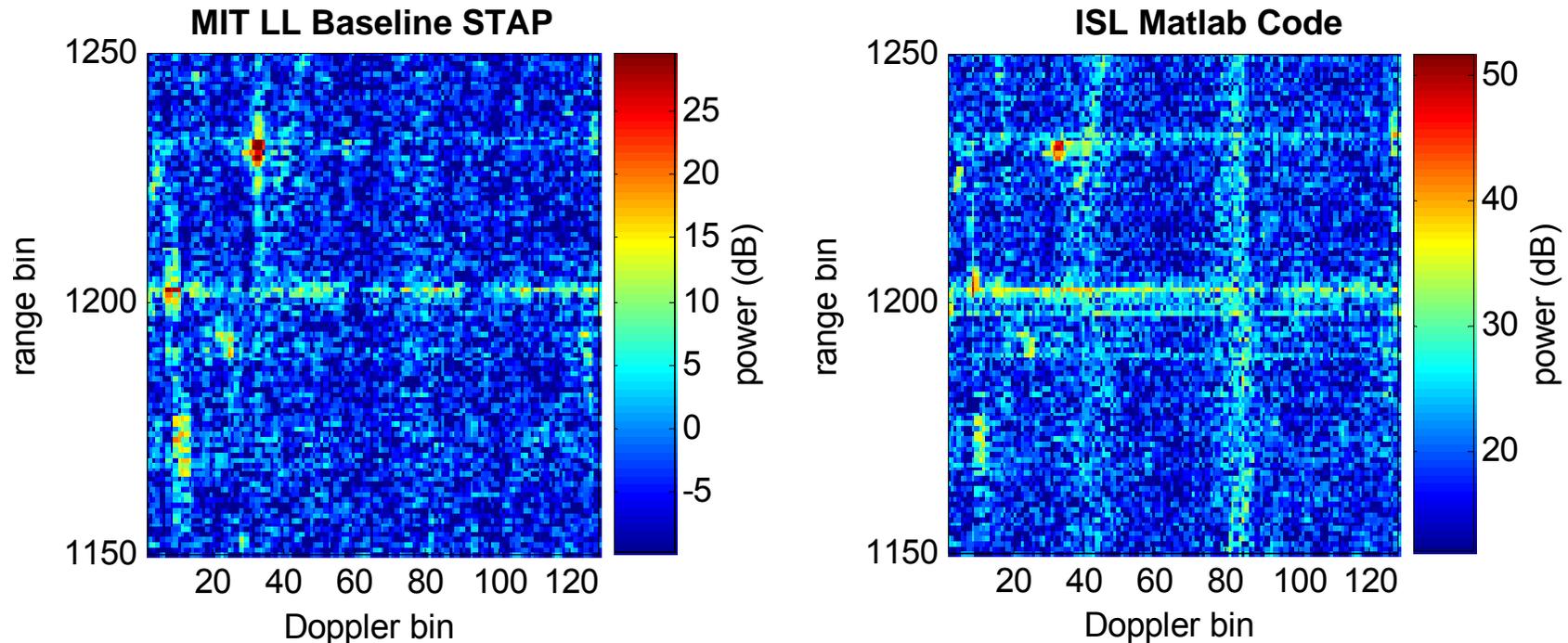
Real-Time Development Tasks

- ✓ • **Set up PVL development environment on ISL Linux cluster**
- **Obtain existing KASSPER real-time testbed STAP source code from MIT Lincoln Laboratory → load, build, and execute using simulated data inputs (ISL received source code 01/05)**
- **Integrate ISL colored loading technique**
 - Choose a colored loading matrix and test with PRI staggered post-Doppler STAP (MATLAB)
 - Code the colored loading matrix calculation in PVL/VS IPL
 - Integrate with STAP code (test and compare with MATLAB version)
- **Demonstrate parallel algorithm on ISL Linux cluster**
 - Define mapping across nodes
 - Execute with simulated and experimental data
 - Test and compare with MATLAB implementation
- **Port to MIT Lincoln Laboratory cluster**
- **Port to KASSPER Mercury test best system**
- **Documentation**

Software Development Environment

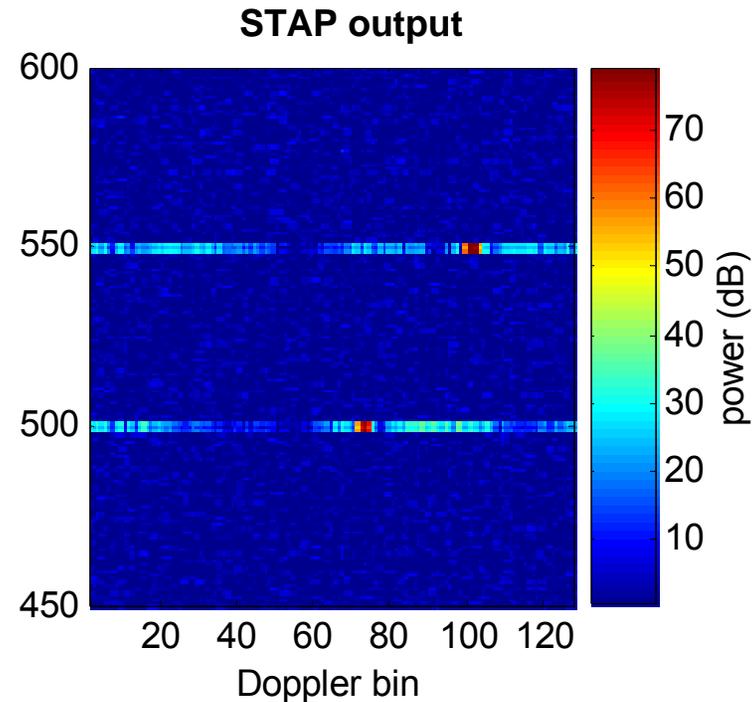
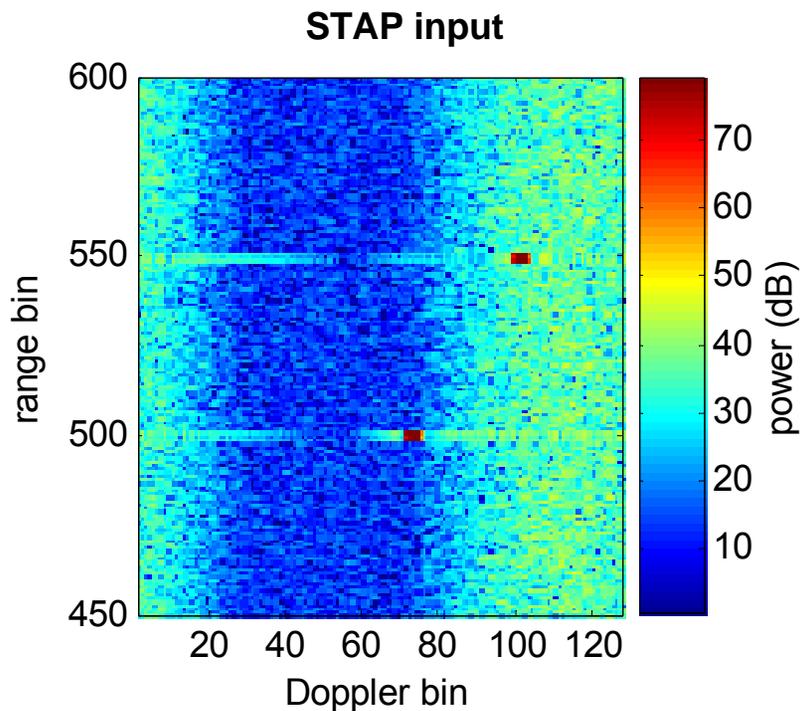


Tuxedo Processing Example



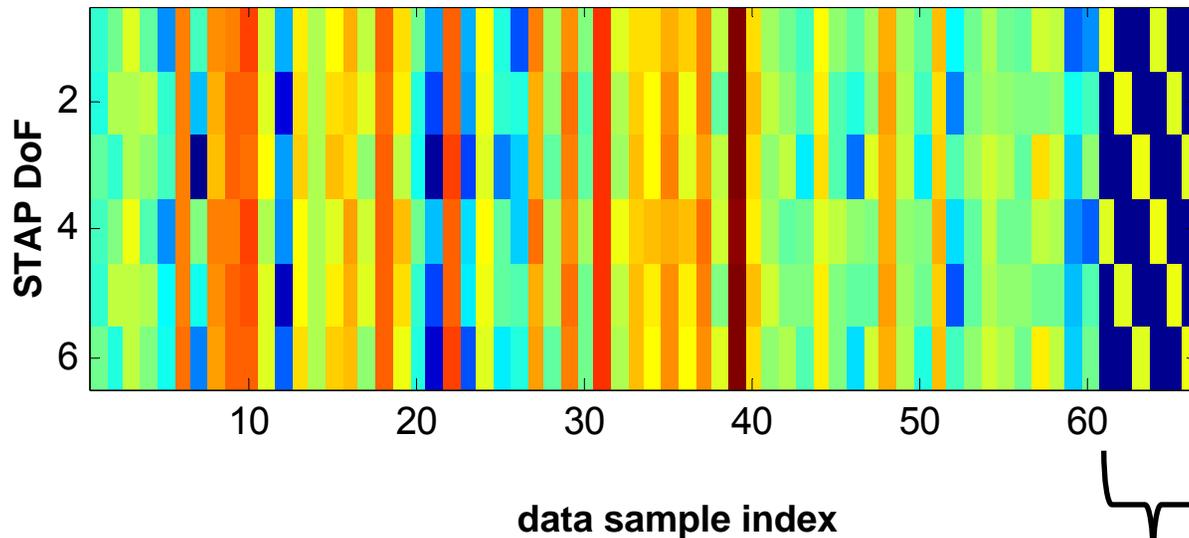
- **Comparison of Tuxedo data processed using KASSPER baseline STAP code (C++) and ISL Matlab STAP algorithm**
 - KASSPER code is PRI-stagger post-Doppler, ISL code is multi-bin post Doppler
 - KASSPER code is AMF normalized, ISL code is normalized to unit gain on white noise
 - Good match between major beamformer residue features
- **Demonstrates we can build and run the code and understand and manipulate the output**

Simulated Data Processing Example



- **A simulated datacube containing clutter and two test targets with same parameters as the Tuxedo data was generated and used as input to the KASSPER code**
- **Demonstrates ability to manipulate the code inputs**
- **Next step is to input KASSPER simulated data sets (e.g., KASSPER data sets 2 and 3)**

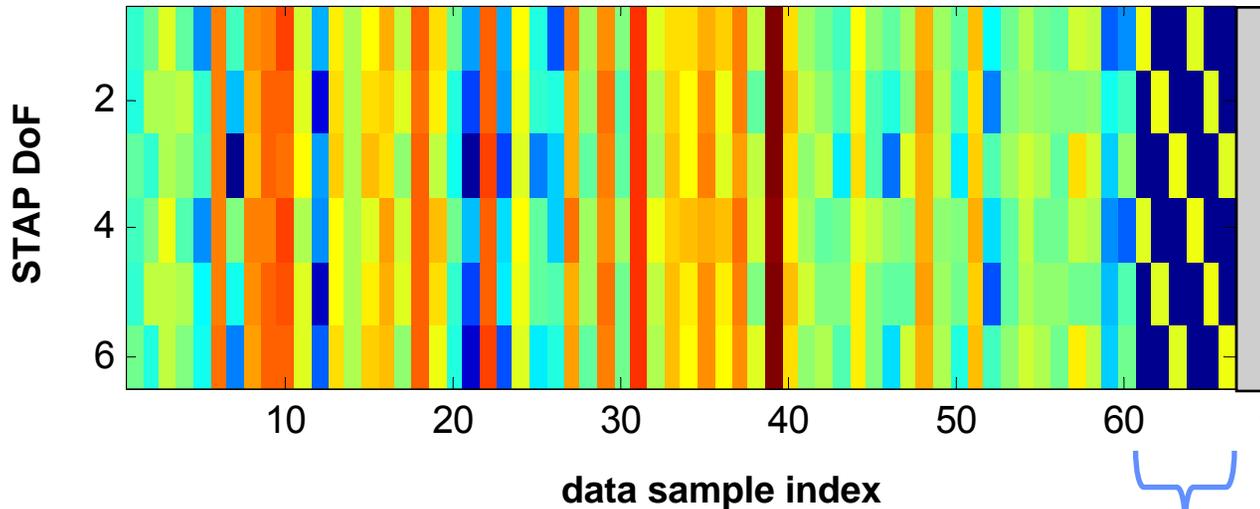
Range Independent Loading



- Matrix augmented to account for diagonal loading
- Not an identity matrix due to correlation between adaptive channels in PRI-stagger algorithm
- Baseline code actually implements “colored” loading → one matrix only, not updated on each CPI

- Example data matrix amplitude output from the KASSPER code for a single Doppler bin shown
- 6 DoFs
 - 3 spatial
 - 2 temporal
- 60 training samples
- Augmented matrix to account for “diagonal” loading visible

Range Dependent Loading



insert distributed clutter loading matrix here

insert small number of vectors to account for each discrete clutter patch → may require QR updating to be efficient

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Future Plans and Summary

- **Colored loading technique has been tested on several simulated and one experimental data set (Tuxedo)**
- **The technique typically leads to fewer false alarms for cases when low sample support is required**
- **Combining colored loading with information derived from conventional beamformer output (or low resolution SAR) shown to help mitigate under-nulling of strong discrete clutter**
- **Future work will focus on detailed analysis/simulation of loading levels → develop rules for setting colored loading levels**
- **Demonstration of colored loading performance will continue using additional simulated data sets and experimental data → movies showing performance over time**
- **Task to implement colored loading on the KASSPER test-bed is underway, including initial evaluation of the existing C++ KASSPER baseline STAP algorithm written using PVL**

Backups

Linear Constraints

- Re-write quadratic constraint using the eigen-decomposition of the *a priori* clutter model, $R_c = U^H D U$ (dominant subspace)

$$\mathbf{w}^H \mathbf{R}_c \mathbf{w} = 0 \Rightarrow \mathbf{w}^H (\mathbf{U} \mathbf{D} \mathbf{U}^H) \mathbf{w} = 0 \Rightarrow (\mathbf{w}^H \mathbf{U}) \mathbf{D} (\mathbf{U}^H \mathbf{w}) = 0$$

$$\Rightarrow \mathbf{w}^H \mathbf{U} = \mathbf{0} \quad \because \mathbf{D} \text{ has strictly positive diagonal elements (also has dimensions } \ll R_c \text{ e.g., Brennan's Rule)}$$

- A set of linear constraints

$$\min_{\mathbf{w}} E\{|\mathbf{w}^H \mathbf{x}|^2\} \quad \text{s.t.} \quad \mathbf{w}^H \mathbf{v} = 1$$

$$\mathbf{w}^H \mathbf{U} = \mathbf{0}$$

$$\mathbf{w}^H \mathbf{w} = \delta$$

desire weights to be orthogonal to *a priori* clutter model

this is the KA part

- Gives:

$$\mathbf{w} = \frac{\bar{\mathbf{R}}_{xx}^{-1} (\mathbf{I} - \mathbf{U} (\mathbf{U}^H \bar{\mathbf{R}}_{xx}^{-1} \mathbf{U})^{-1} \mathbf{U}^H \bar{\mathbf{R}}_{xx}^{-1}) \mathbf{v}}{\mathbf{v}^H \bar{\mathbf{R}}_{xx}^{-1} (\mathbf{I} - \mathbf{U} (\mathbf{U}^H \bar{\mathbf{R}}_{xx}^{-1} \mathbf{U})^{-1} \mathbf{U}^H \bar{\mathbf{R}}_{xx}^{-1}) \mathbf{v}} = \frac{\bar{\mathbf{R}}_{xx}^{-1} \mathbf{P} \mathbf{v}}{\mathbf{v}^H \bar{\mathbf{R}}_{xx}^{-1} \mathbf{P} \mathbf{v}}$$

$$\bar{\mathbf{R}}_{xx} = \mathbf{R}_{xx} + \beta_L \mathbf{I}$$

Quadratic vs. Linear Constraints

- The two solutions:

$$\mathbf{w} = \frac{(\bar{\mathbf{R}}_{xx} + \beta_d \mathbf{R}_c)^{-1} \mathbf{v}}{\mathbf{v}^H (\bar{\mathbf{R}}_{xx} + \beta_d \mathbf{R}_c)^{-1} \mathbf{v}} \quad \mathbf{w} = \frac{\bar{\mathbf{R}}_{xx}^{-1} \mathbf{P} \mathbf{v}}{\mathbf{v}^H \bar{\mathbf{R}}_{xx}^{-1} \mathbf{P} \mathbf{v}}$$

- Manipulation of the quadratic constraint solution using the matrix inversion lemma and eigen-decomposition highlights the difference between the two solutions

$$\bar{\mathbf{R}}_{xx}^{-1} \mathbf{P} = \bar{\mathbf{R}}_{xx}^{-1} (\mathbf{I} - \mathbf{U} (\mathbf{U}^H \bar{\mathbf{R}}_{xx}^{-1} \mathbf{U})^{-1} \mathbf{U}^H \bar{\mathbf{R}}_{xx}^{-1})$$

$$(\bar{\mathbf{R}}_{xx} + \beta_d \mathbf{R}_c)^{-1} = \bar{\mathbf{R}}_{xx}^{-1} (\mathbf{I} - \mathbf{U} (\mathbf{U}^H \bar{\mathbf{R}}_{xx}^{-1} \mathbf{U} + \frac{1}{\beta_d} \mathbf{D}^{-1})^{-1} \mathbf{U}^H \bar{\mathbf{R}}_{xx}^{-1})$$

- The two solutions are equivalent in the limit of infinite loading and/or large clutter model eigenvalues
- Since the linear constraints cause the weights to be precisely orthogonal to the known covariance the quadratic constraint achieves this constraint only approximately