

# Terrain Knowledge Assisted STAP

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# Agenda

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- Problem Addressed
- Conventional STAP
- Environmental Based Clutter Modeling
- Environmental Based STAP
  - Fully Adaptive KASSPER
  - Partially Adaptive KASSPER
- Conclusions
- Current Status and Results
- New Issues to be Addressed

## **Problem Addressed**

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- **Real-world radar clutter may be nonstationary.**
- **Actual data may not be available or too few samples.**
- **Pre-available resource (maps, images) can be used.**
- **Terrain images can be used for clutter generation and reconstruction of the weight vector.**
- **This may improve terrain assisted performance modeling techniques.**
- **Useful in a limited sample support scene.**
- **Four different methods are addressed.**

# Conventional STAP Detection

## Spatio-Temporal Steering Vector:

$$\mathbf{a} = \mathbf{a}(\theta, \omega_d) = \mathbf{b}_M(\omega_d) \otimes \mathbf{a}_N(\theta)$$

$$\mathbf{a}_N(\theta) = \begin{bmatrix} 1 \\ e^{-j\pi \sin \theta} \\ \vdots \\ e^{-j\pi(N-1)\sin \theta} \end{bmatrix}, \quad \mathbf{b}_M(\omega_d) = \begin{bmatrix} 1 \\ e^{-j\pi\omega_d} \\ \vdots \\ e^{-j2\pi(M-1)\omega_d} \end{bmatrix}$$

Find weight vector  $\mathbf{w}$  so that

$$Z = \left| \mathbf{w}^* \mathbf{x}_r \right| \begin{array}{l} \text{Yes} \\ > \\ < \\ \text{No} \end{array} \eta$$

$\mathbf{x}_r$  : data vector of size  $MN$

$M$ : Number of pulses

$N$ : Number of sensors

can be used for threshold detection optimally.

# Conventional STAP Detection

Maximize output signal to interference plus noise ratio (SINR).

- **Optimum weight vector:  $\mathbf{R} \Rightarrow \mathbf{w}$**
- **$\mathbf{R}$  is  $MN \times MN$  and usually unknown.**
- **In practice, unknown  $\mathbf{R}$  needs to be estimated from the available sample snapshots.**
- **Optimum estimation of  $\mathbf{R}$  from  $K$  independent sample snapshots**

$$\hat{\mathbf{R}} = \frac{1}{K} \sum_k \mathbf{x}_k \mathbf{x}_k^*$$

# Generation of Realistic Clutter Data

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## Resource:

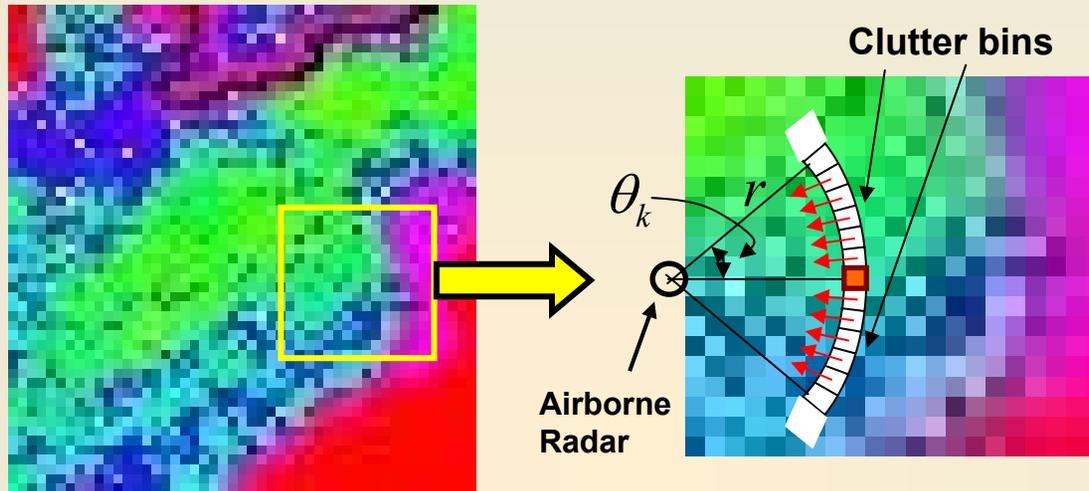
- Image intensity, geodetic data (NASA/NIMA data)
- Terrain spectral characteristics

## Solution:

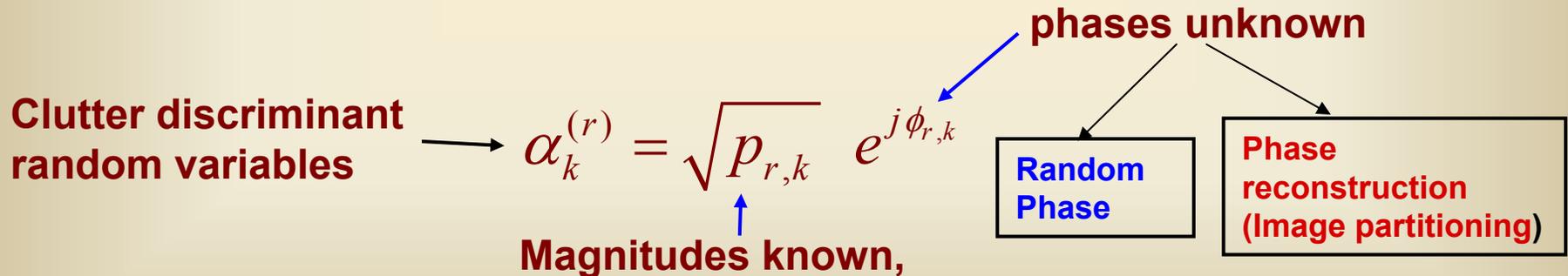
- Images give magnitude of the clutter discrete
- Global terrain can be partitioned into different regions...
- Reconstruct clutter phases using convex projection methods and terrain type from image

# NASA's Multidisciplinary Data (MODIS)

[ftp://modis.gsfc.nasa.gov/pub/Data\\_Sets/outgoing/Data\\_Sets/CD/land/JPG/TREE\\_COVER/MOD44B\\_TreeCover\\_2001.jpg](ftp://modis.gsfc.nasa.gov/pub/Data_Sets/outgoing/Data_Sets/CD/land/JPG/TREE_COVER/MOD44B_TreeCover_2001.jpg)



When an image is given, suggest a way to determine clutter discrete.  
For different regions, phase information needs to be reconstructed.



# Terrain Knowledge Based STAP

The clutter from  $r$ -th range bin at the airborne platform

$$\mathbf{x}_r = \sum_k \alpha_k^{(r)} \mathbf{a}(\theta_k, \omega_{d_k})$$

$\alpha_k^{(r)}$  : Clutter  
Discrete

$\mathbf{a}(\theta_k, \omega_{d_k})$  : Steering Vector for  
 $k$ -th clutter bin

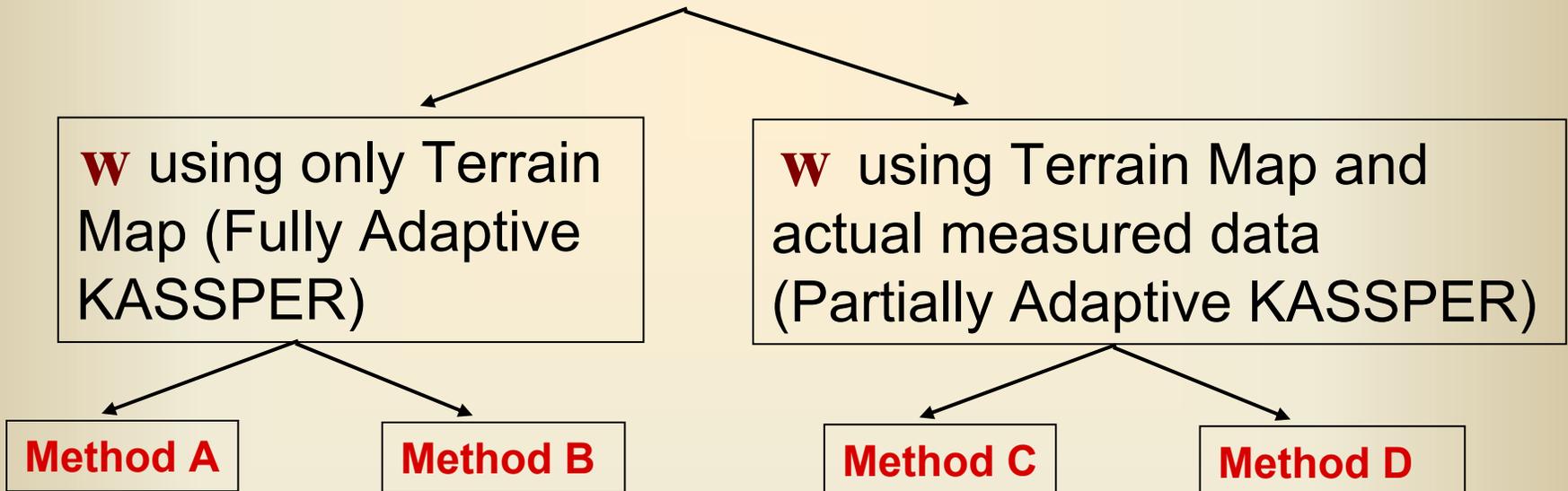
- Quality of the clutter discrete depends on the environment (geodetic data)
- Type of terrain information is critical (eg. Forest, Ocean, Desert, etc.) for clutter generation
- Realistic clutter data is required for performance analysis of STAP algorithms
- How to generate a realistic clutter discrete?

# Terrain Knowledge Based STAP

Use Terrain Image Map to Compute STAP Weight Vector  $\mathbf{w}$

- How to accommodate terrain map intensity images (eg. NASA MODIS public domain data) in computing STAP weight vector  $\mathbf{w}$  a-priori?

## Terrain Knowledge Based STAP



# Terrain Knowledge Based STAP

## I. Fully Adaptive KASSPER

### Method A :

Computes the clutter covariance matrix using the images

### Method B :

Generates data from images and then estimates the clutter covariance matrix

## II. Partially Adaptive KASSPER

### Method C (Weight Vector Update):

Combines the ideal weight vector from Method A together with the estimated weight vector from measured data.

### Method D (Covariance Matrix Update) :

Combines the ideal clutter covariance matrix from Method A together with the estimated clutter covariance matrix from measured data.

# Terrain Knowledge Based STAP

- Fully Adaptive KASSPER: (Uses Only Terrain Map)

## Method A: Covariance matrix from images:

Compute the ideal clutter covariance matrix from image intensity and aircraft-earth geometry

$$\mathbf{R}_A = \sum_k p_k \mathbf{a}_k \mathbf{a}_k^*$$

Image Intensity                      Steering vector

Use this covariance matrix to compute the weight vector

$$\mathbf{R}_A \Rightarrow \mathbf{w}_A$$

# Terrain Knowledge Based STAP

- Fully Adaptive KASSPER: (Uses Only Terrain Map)

## Method B: Generate data from images and estimate clutter covariance matrix

Generate the data using image intensity and aircraft-earth geometry

$$\mathbf{x} = \sum_k \sqrt{p_k} e^{j\phi_k} \mathbf{a}_k \mathbf{a}_k^*$$

Image intensity  $\uparrow$   $\sqrt{p_k}$

Steering vector  $\uparrow$   $\mathbf{a}_k$

Random phase is used under the assumption of uncorrelated clutter  $\rightarrow$   $e^{j\phi_k}$

Estimate clutter covariance matrix from data:

$$\hat{\mathbf{R}}_B = \frac{1}{K} \sum_k \mathbf{x}_k \mathbf{x}_k^*$$

Use this covariance matrix to compute the weight vector

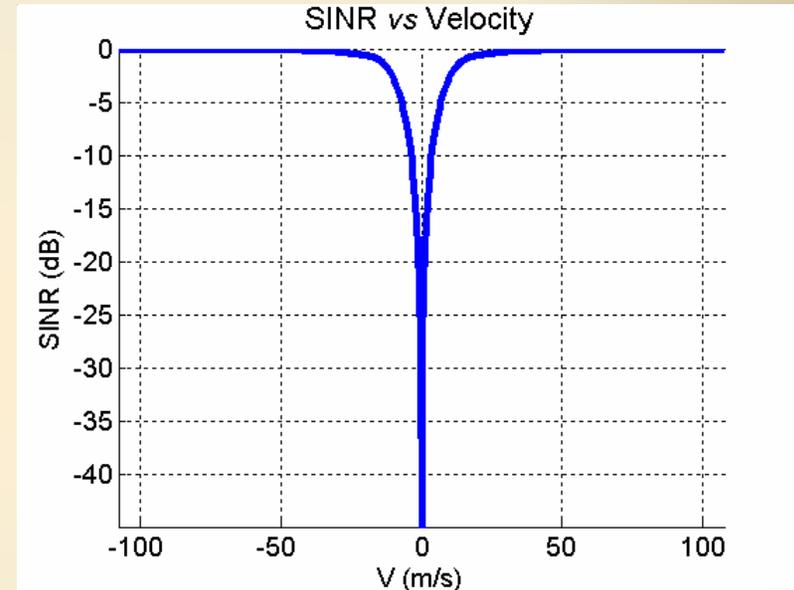
$$\hat{\mathbf{R}}_B \Rightarrow \hat{\mathbf{w}}_B$$

# Illustration Parameters

$$SINR_{Ideal} = \mathbf{a}(\theta_t, \omega_d)^* \mathbf{R}^{-1} \mathbf{a}(\theta_t, \omega_d)$$

$$SINR = \frac{|\hat{\mathbf{w}}^* \mathbf{a}(\theta_t, \omega_d)|^2}{\hat{\mathbf{w}}^* \mathbf{R}^{-1} \hat{\mathbf{w}}}$$

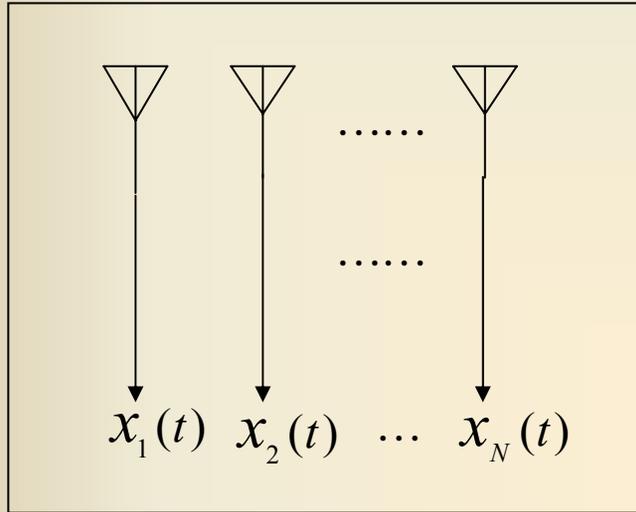
**Doppler:**  $\omega_d = \frac{2V T_r}{\lambda / 2}$



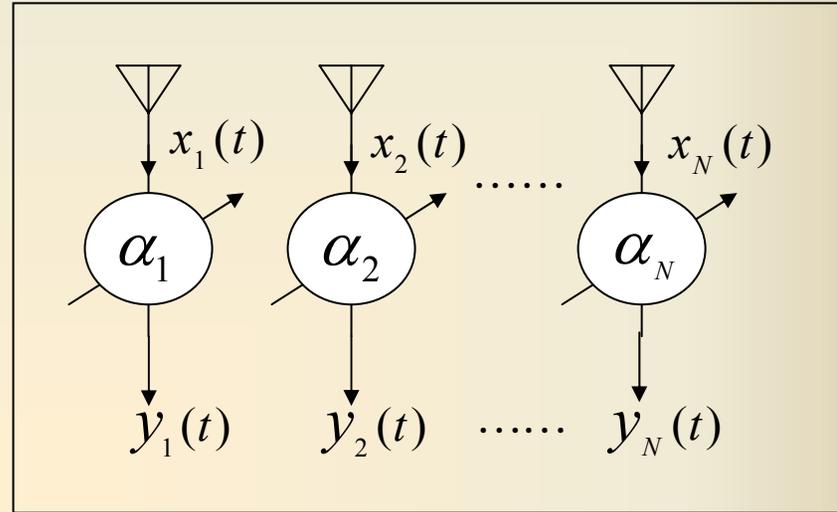
**Sample Matrix Inversion with Diagonal Loading (SMIDL)**

**Covariance Matrix Tapering (CMT)**

# Covariance Matrix Tapering



(a) Traditional Array



(b) Tapered Array

Tapering an array:  $\hat{\mathbf{R}}_T = \hat{\mathbf{R}} \odot T$

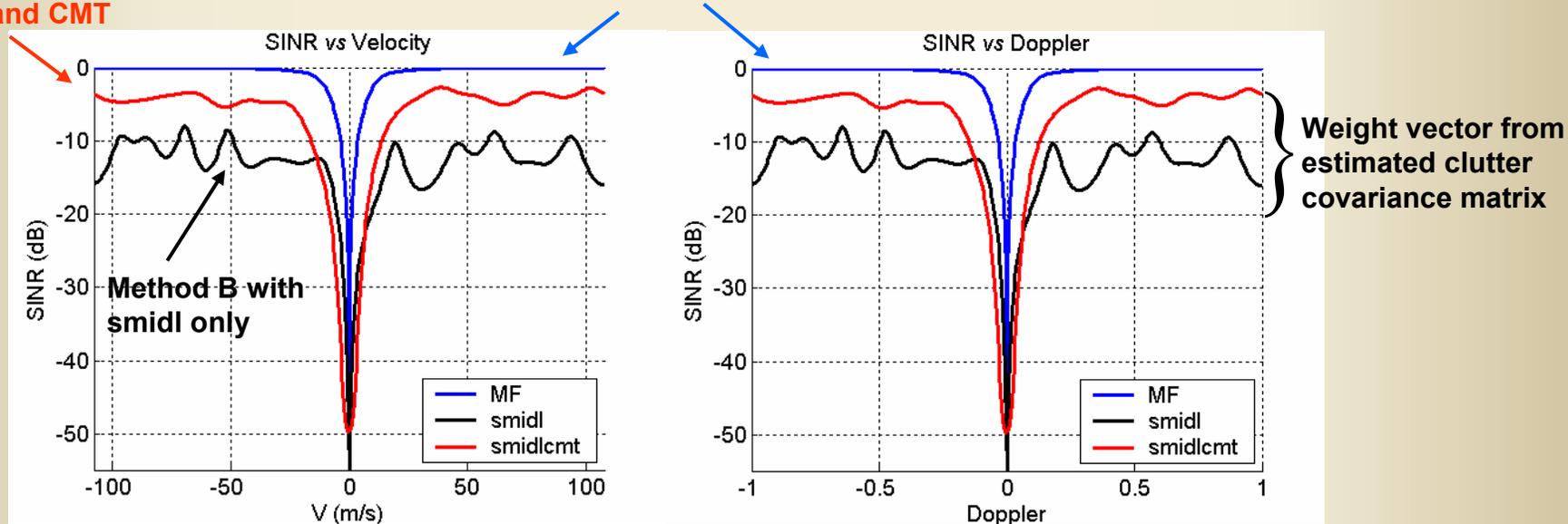
where  $T$  is a tapering matrix and  $\hat{\mathbf{R}}$  is the original estimate

# Clutter Suppression using CMT

Number of sensors = 14, Number of pulses = 16, Radar operating frequency = 435 MHz, Inter-element spacing = half wavelength, CNR = 40 dB, Number of samples = 30

Method B with smidl and CMT

Method A: Weight vector from ideal clutter covariance matrix

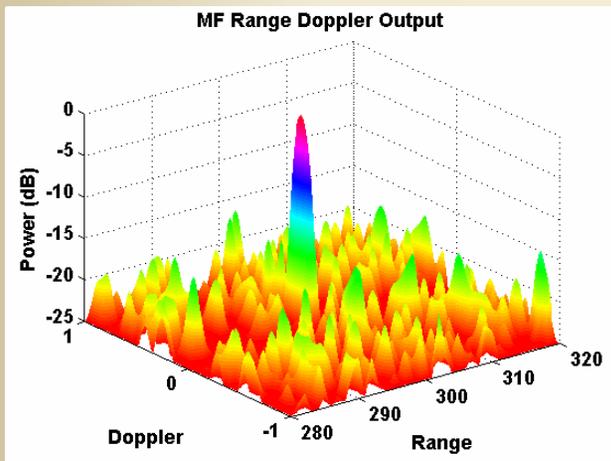


Clutter suppression with ( --- ) and without (---) CMT

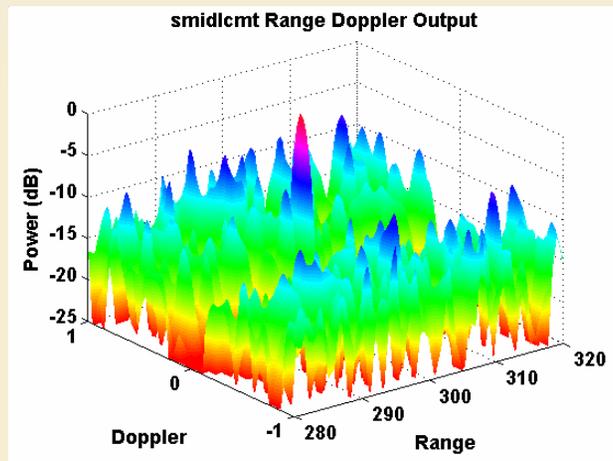
The figures above are generated from synthesized clutter data using NASA image intensity for the New York tri-state area along with reconstructed phases for a specific airborne configuration. CMT boosting on estimated covariance matrix gives better clutter suppression the smidl alone.

# Target Detection Performance

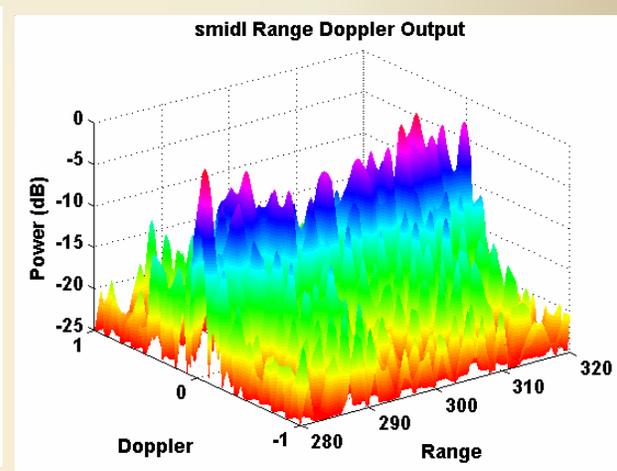
Target Location = 300<sup>th</sup> range bin, Target azimuth = 0°, SNR = 0 dB, Target Doppler = 0.2, Number of samples used for estimated Cov. Matrix = 30



Method A



Method B with  
smidl and CMT



Method B with  
smidl

The figures above are generated from synthesized clutter data with target injected at a single range bin. In practice, one data will be collected and will be interrogated with the synthetic weight vector to detect target. Method A using ideal clutter covariance matrix gives the best performance. CMT boosting on estimated covariance matrix gives improved target detection.

# Terrain Knowledge Based STAP

## Partially Adaptive KASSPER:

### Use a-priori information together with actual measurements

- Image gives the prior terrain information, actual data depends on other factors such as when the data is collected, weather, etc...
- Actual data from measurement is related to the prior terrain information with some variations.
- To account for these variations, the data can be generated using the image plus an additional component.

The actual measurement is simulated as follows:

Magnitude and phase depend on images, the prior information.

$$\mathbf{x} = \beta \sum_{k(l,m)} \sqrt{p_{k(l,m)}} e^{j\phi_{k(l,m)}} \mathbf{a}_k \mathbf{a}_k^* + (1 - \beta) \sum_i \sqrt{Q_i} e^{j\psi_i} \mathbf{a}_i \mathbf{a}_i^*, \quad 0 \leq \beta \leq 1$$

Weight Factor

Unknown magnitude and phase depend on the actual measurement.

# Partial KASSPER – Obtain Weight Vector from Priori Information and Actual Measurement

- Terrain image gives the ideal clutter covariance matrix  $\mathbf{R}_A$  using

$$\mathbf{R}_A = \sum_k p_k \mathbf{a}_k \mathbf{a}_k^*$$

This provides the ideal weight vector to be :  $\mathbf{R}_A \Rightarrow \mathbf{w}_A$

- Actual data measurement gives the estimated clutter covariance matrix  $\hat{\mathbf{R}}$  using

$$\hat{\mathbf{R}} = \frac{1}{K} \sum_k \mathbf{x} \mathbf{x}^*$$

This gives the estimated weight vector:  $\hat{\mathbf{R}} \Rightarrow \hat{\mathbf{w}}$

**How to make use of both priori information and actual measurement?**

# Partial KASSPER

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- **Method C (Weight Vector Update) :**

Combine the ideal weight vector  $\mathbf{w}_A$  from Method A together with the estimated weight vector  $\hat{\mathbf{w}}$  from data.

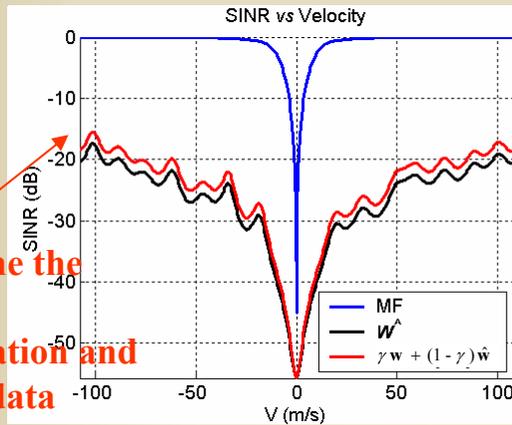
$$\mathbf{w}_C = \gamma \mathbf{w}_A + (1 - \gamma) \hat{\mathbf{w}}, \quad 0 \leq \gamma \leq 1$$

Weight factor  $\gamma$  determines the dependency of the prior information.

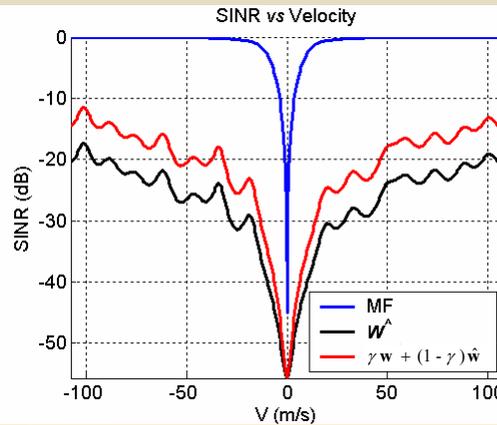
When  $\gamma$  increases, the weight vector  $\mathbf{w}_C$  dependency on the prior information increases.

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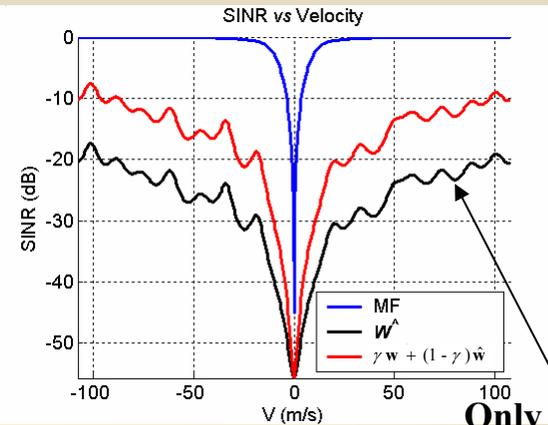
# Method C -- Clutter Suppression Performance



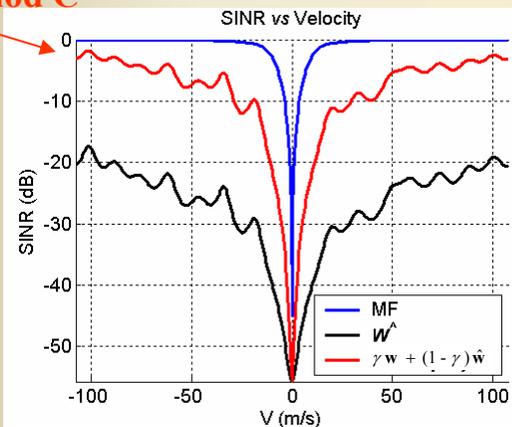
(a)  $\gamma = 0.2$



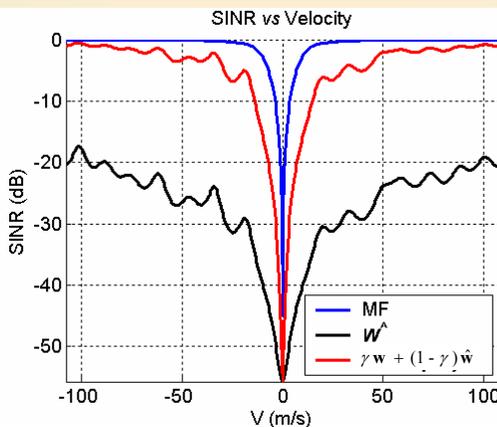
(b)  $\gamma = 0.5$



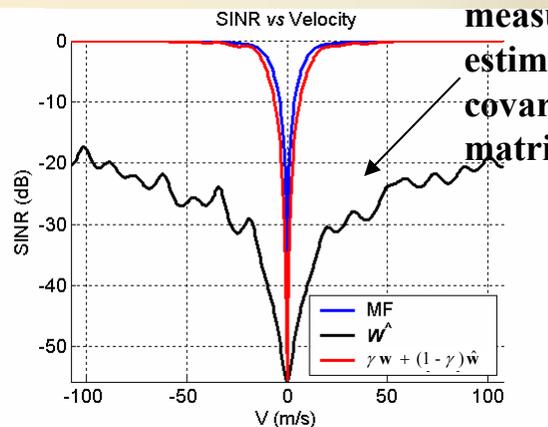
(c)  $\gamma = 0.7$



(d)  $\gamma = 0.9$



(e)  $\gamma = 0.95$



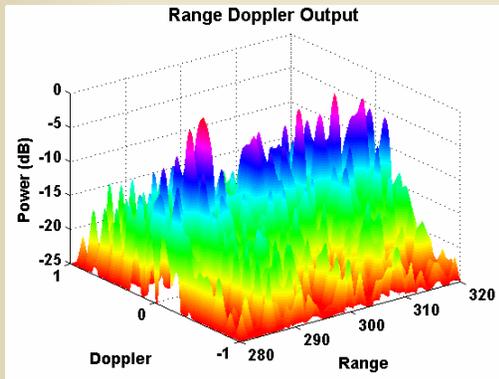
(f)  $\gamma = 0.99$

Combine the prior information and actual data measurement as in Method C

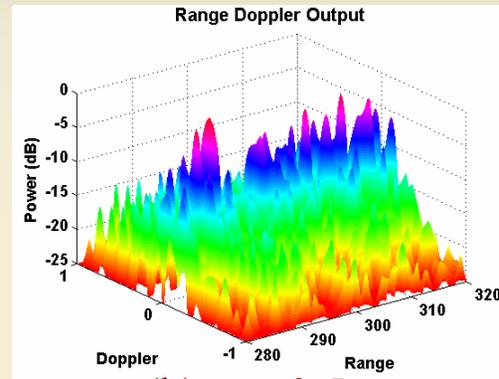
Only use the actual data measurement to estimate clutter covariance matrix

Combining the prior information gives better performance. Large percentage ( $\gamma = 0.95$ ) of the prior information is required for acceptable improvement on clutter suppression performance.

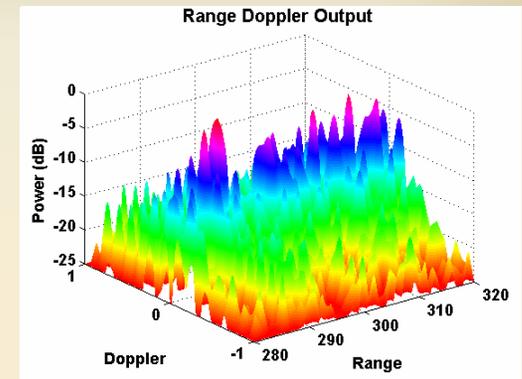
# Method C – Target Detection Performance



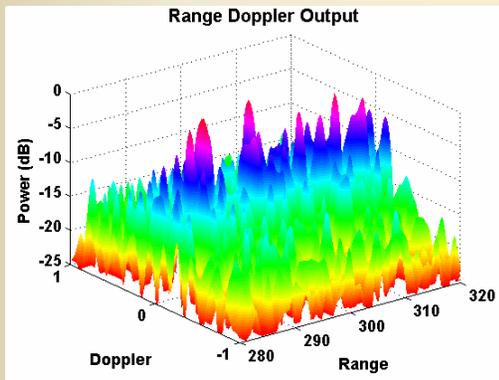
(a)  $\gamma = 0.2$



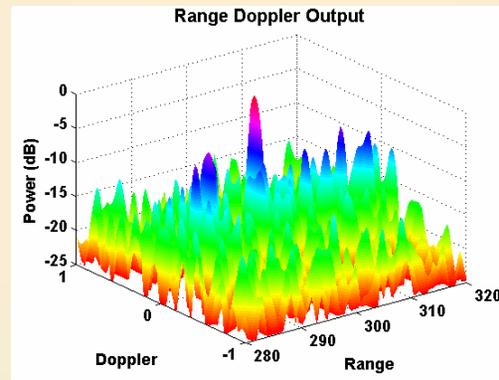
(b)  $\gamma = 0.5$



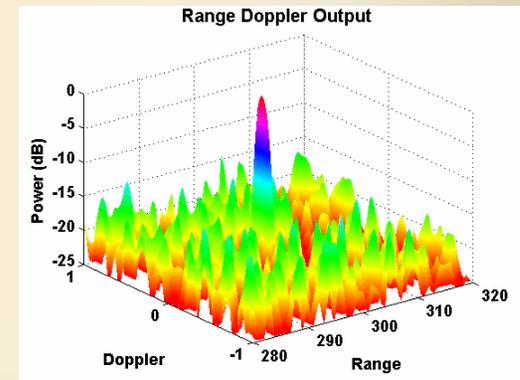
(c)  $\gamma = 0.7$



(d)  $\gamma = 0.9$



(e)  $\gamma = 0.95$



(f)  $\gamma = 0.99$

Target Location = 300<sup>th</sup> range bin, Target azimuth = 0°, SNR = 0 dB, Target Doppler = 0.2, Number of Samples used: 26

Large percentage of prior information is needed to detect target.

# Partial KASSPER

- **Method D (Covariance Matrix Update):**

Combine the ideal clutter covariance matrix  $\mathbf{R}_A$  from Method A together with the estimated clutter covariance matrix  $\hat{\mathbf{R}}$  from data.

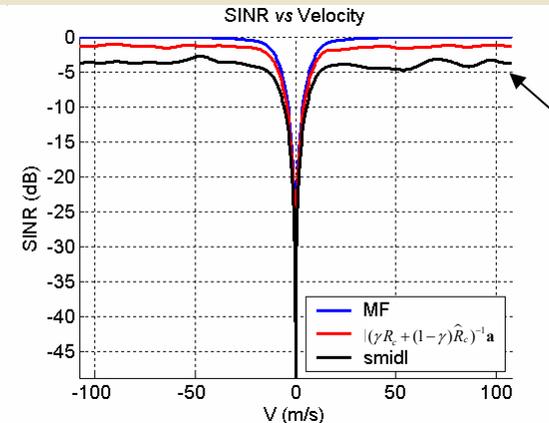
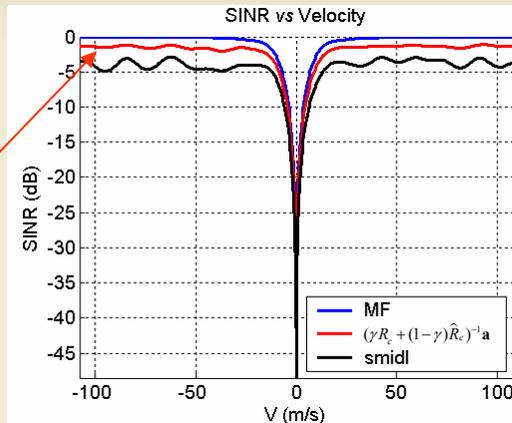
$$\mathbf{R}_D = \gamma \mathbf{R}_A + (1 - \gamma) \hat{\mathbf{R}}, \quad 0 \leq \gamma \leq 1$$

$$\mathbf{R}_D \Rightarrow \mathbf{w}_D$$

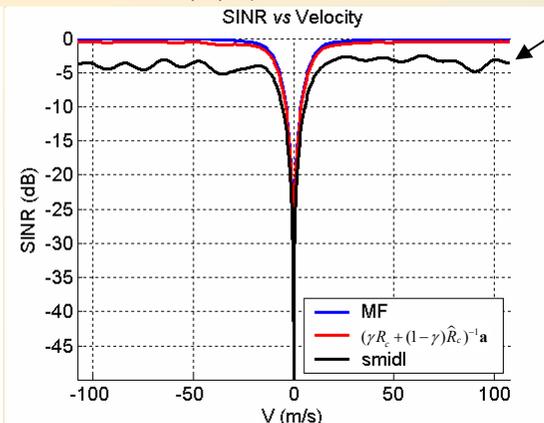
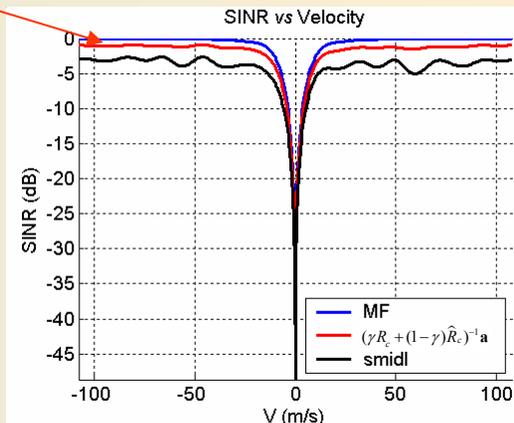
Weighting factor  $\gamma$  sets the dependency of the prior information. When  $\gamma$  increases, the weight vector  $\mathbf{w}_D$  dependency on the prior information also increases.

# Partial KASSPER Method D -- Clutter Suppression Performance

Combine the prior information and actual data measurement as in Method D

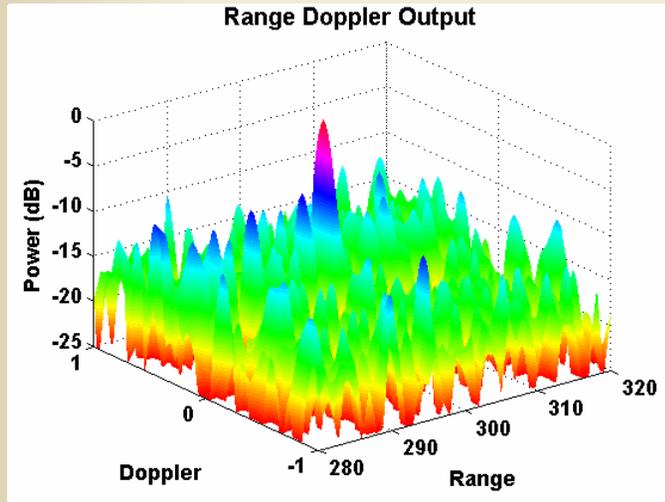


Only use the actual data measurement to estimate clutter covariance matrix

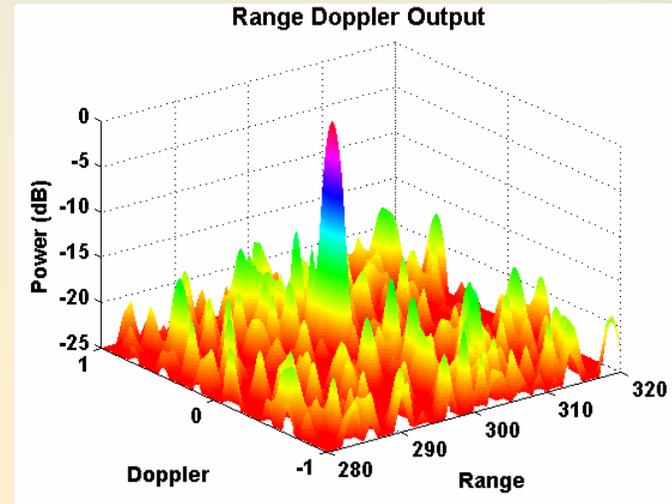


Combining the prior information gives better performance. Only a small percentage ( $\gamma = 0.01$ ) of the prior information is required for improved clutter suppression.

# Partial KASSPER Method D – Target Detection Performance



(a) smidl using the actual measurement with 40 data samples



(b) Method D ( $\gamma = 0.1$ )

**Target Location = 300<sup>th</sup> range bin, Target azimuth = 0°, SNR = 0 dB,  
Target Doppler = 0.2**

**Combining prior information gives better target detection performance**

# Conclusions

- For uncorrelated data fully adaptive KASSPER can be used.
- For correlated data partial KASSPER should be used.
  - Method A cannot be used
  - Phase reconstruction is required for clutter generation
- Performance improvement is noticeable when a-priori terrain information is utilized.
- Target detection performance is also dependent on the quality of the image.

# Current Status and Results

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- **Generated terrain specific clutter data using terrain scene from NASA MODIS data for New York Tri-State Region**
- **Preliminary performance analysis of STAP techniques are investigated.**
- **Quantified *SINR* performance analysis on the generated terrain specific data.**
- **Four different methods for clutter suppression are analyzed.**

# Terrain Knowledge STAP – New Issues to be addressed

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- **Generate appropriate clutter data using terrain scenes from different data scenes.**
- **Quantify performance analysis of Covariance Matrix Tapering effects on the generated data.**
- **Investigate different methods to reconstruct clutter discrete from terrain information.**
- **For correlated data, how to reconstruct unknown phase for clutter discrete.**
- **Utilizing the clutter data generated using the geodetic information, conduct performance analysis to determine the limitations of GMTI applications.**