SPARSITY-BASED SPACE-TIME ADAPTIVE PROCESSING FOR AIRBORNE RADAR WITH COPRIME ARRAY AND COPRIME PULSE REPETITION INTERVAL
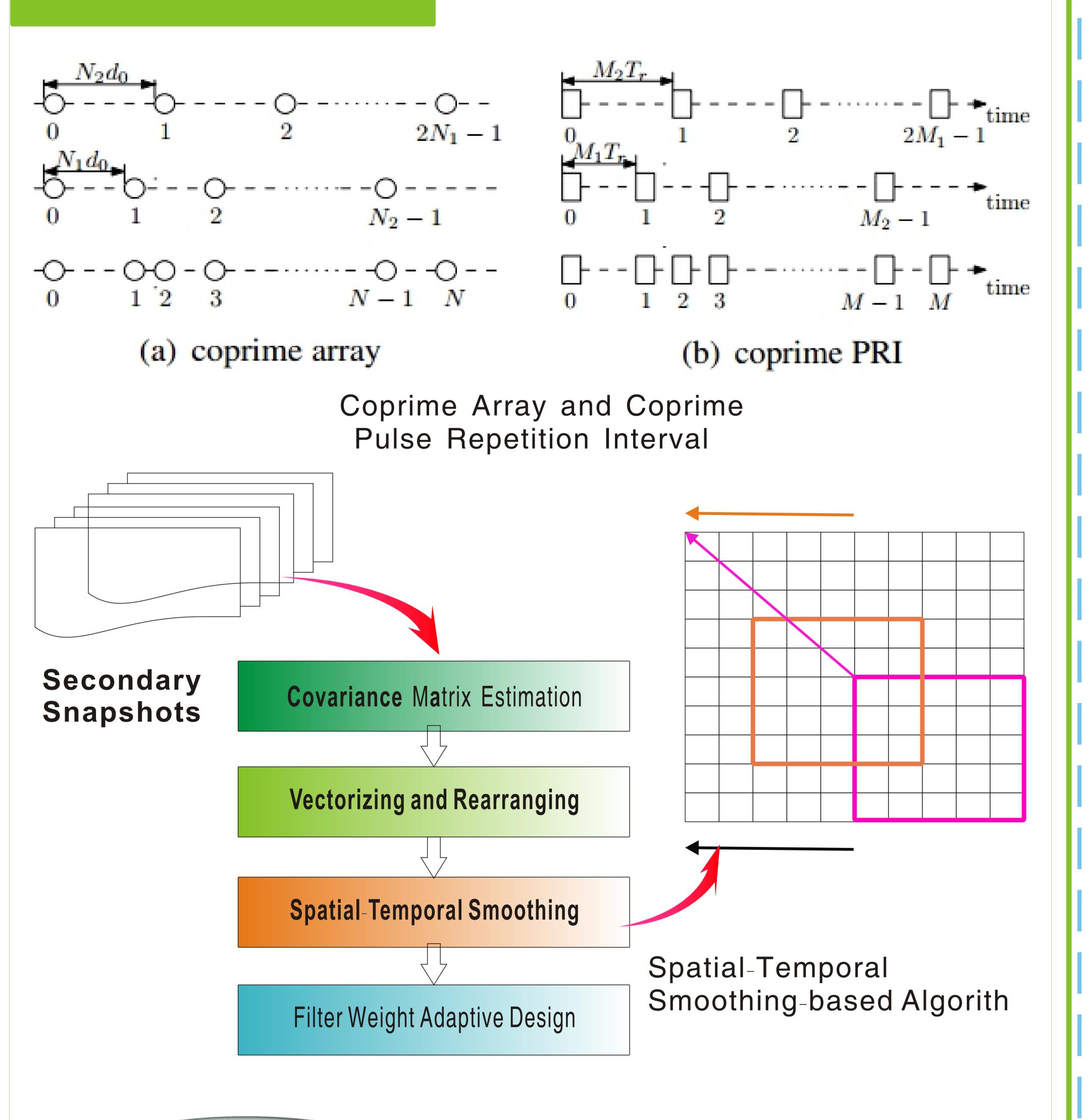
X. Wang, Z. Yang, and J. Huang
Shenzhen University

Objectives

- To efficiently exploit the degrees of freedom (DoFs) offered by coprime configuration;

- To improve the convergence by exploiting sparsity of clutter spectrum.

Related Works

(a) coprime array   (b) coprime PRI

Coprime Array and Coprime Pulse Repetition Interval

Secondary Snapshots

- Covariance Matrix Estimation
- Vectorizing and Rearranging
- Spatial Temporal Smoothing
- Filter Weight Adaptive Design

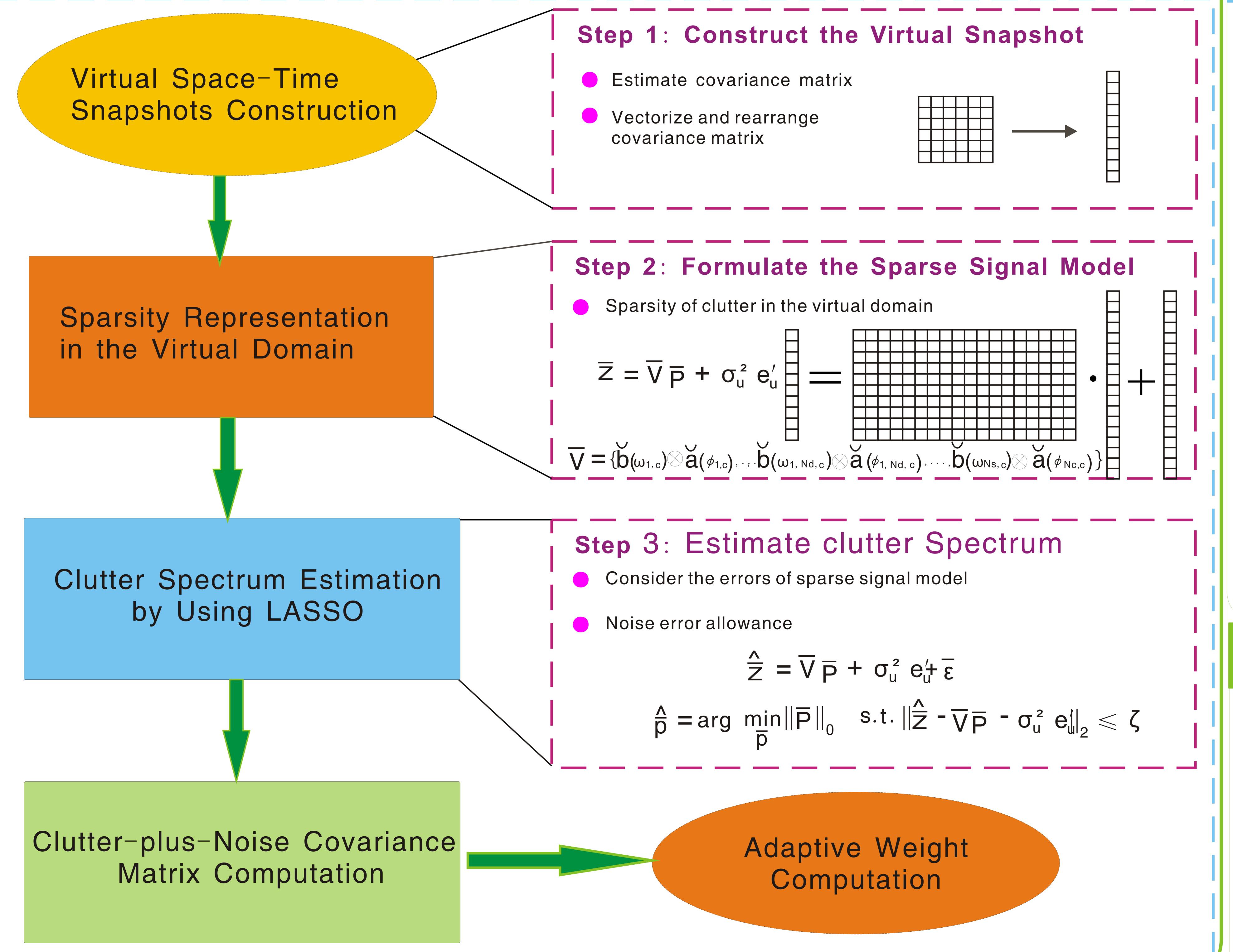Spatial-Temporal Smoothing-based Algorithm

Problems

- Slow convergence for the spatial-temporal Smoothing-based algorithm;

- As the number of DoFs utilized by the spatial-temporal smoothing-based algorithm is just the half of the whole virtual DoFs.

Proposed Sparsity-based Algorithm

Basic idea:

- Design space-time adaptive processing algorithm in virtual domain is considered without the spatial-temporal smoothing technique;

- Using the high resolution ability of sparse recovery technique and the spasity of clutter spectrum to improve convergence of the proposed algorithm.

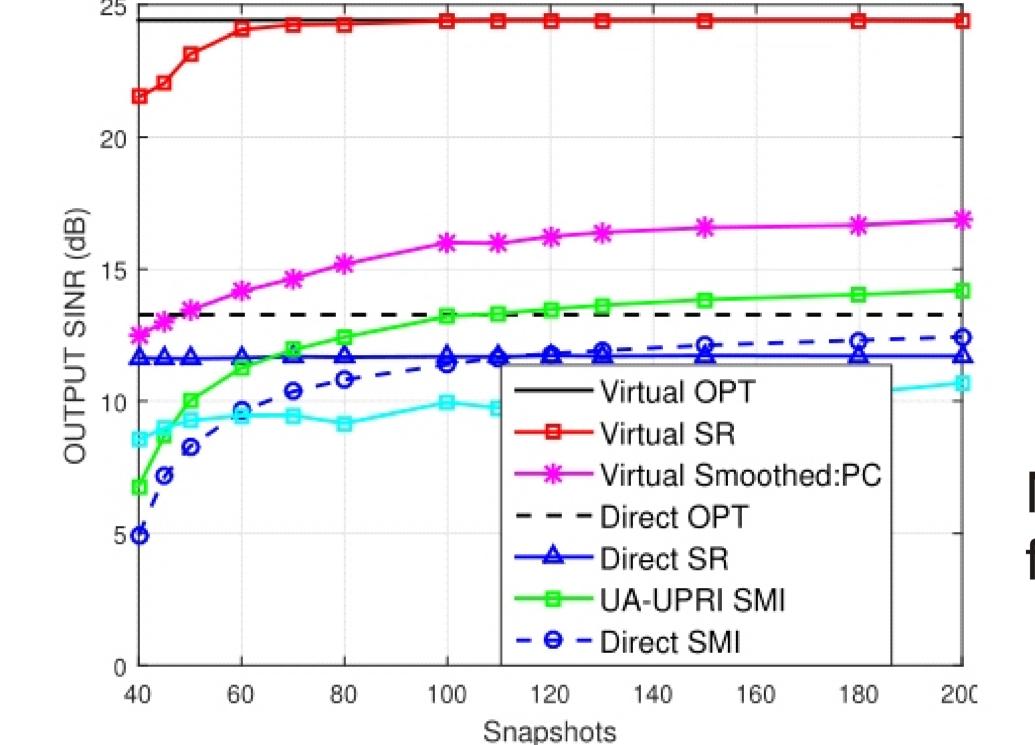**Virtual Space-Time Snapshots Construction**

Step 1: Construct the Virtual Snapshot

- Estimate covariance matrix

- Vectorize and rearrange covariance matrix

Sparsity Representation in the Virtual Domain

Step 2: Formulate the Sparse Signal Model

- Sparsity of clutter in the virtual domain

$$\overline{z} = \overline{V}\,\overline{p} + \sigma_u^2\, e_u'$$

$$\overline{V} = \{\breve{b}_{(\omega_{1,c})} \otimes \breve{a}_{(\phi_{1,c})} \ldots \breve{b}_{(\omega_{1,Nd,c})} \otimes \breve{a}_{(\phi_{1,Nd,c})} \ldots \breve{b}_{(\omega_{Ns,c})} \otimes \breve{a}_{(\phi_{Nc,c})}\}$$

Clutter Spectrum Estimation by Using LASSO

Step 3: Estimate clutter Spectrum

- Consider the errors of sparse signal model

- Noise error allowance

$$\hat{\overline{z}} = \overline{V}\,\overline{p} + \sigma_u^2\, e_u' + \overline{\varepsilon}$$

$$\hat{\overline{p}} = \arg\min_{\overline{p}} \|\overline{p}\|_0 \quad \text{s.t.} \quad \|\hat{\overline{z}} - \overline{V}\,\overline{p} - \sigma_u^2\, e_u'\|_2 \leqslant \zeta$$

Clutter-plus-Noise Covariance Matrix Computation

Adaptive Weight Computation

Experimental Results

Senarios:

Number of Sensors	6(Coprime Factors:2,3)	Minimal Spacing	Half-wavelength
Number of Pulses	6(Coprime Factors:2,3)	Minimal PRI	4000Hz
Velocity of Platform	125m/s	Clutter-to-Noise Ratio	40dB
Carrier Frequency	2.4GHz	Ratio Coefficient	4

Noise error allowance:

$$\zeta = \sqrt{\text{Var}(\overline{\varepsilon})}$$

$$\overline{\varepsilon} \sim CN\left(0, \frac{1}{N} H^{-1}(R^T \otimes R)(H^{-1})^H\right)$$

Note: H is a transforming matrix which involves virtual and rearranging process. 'Var( )' denotes the variance operator.
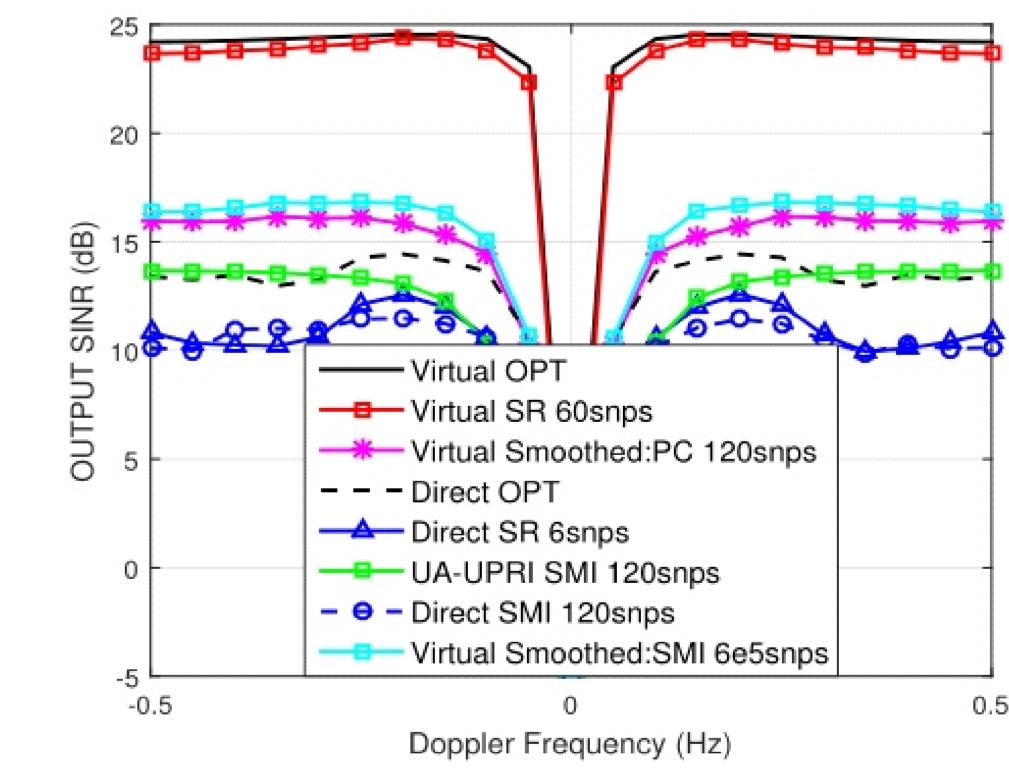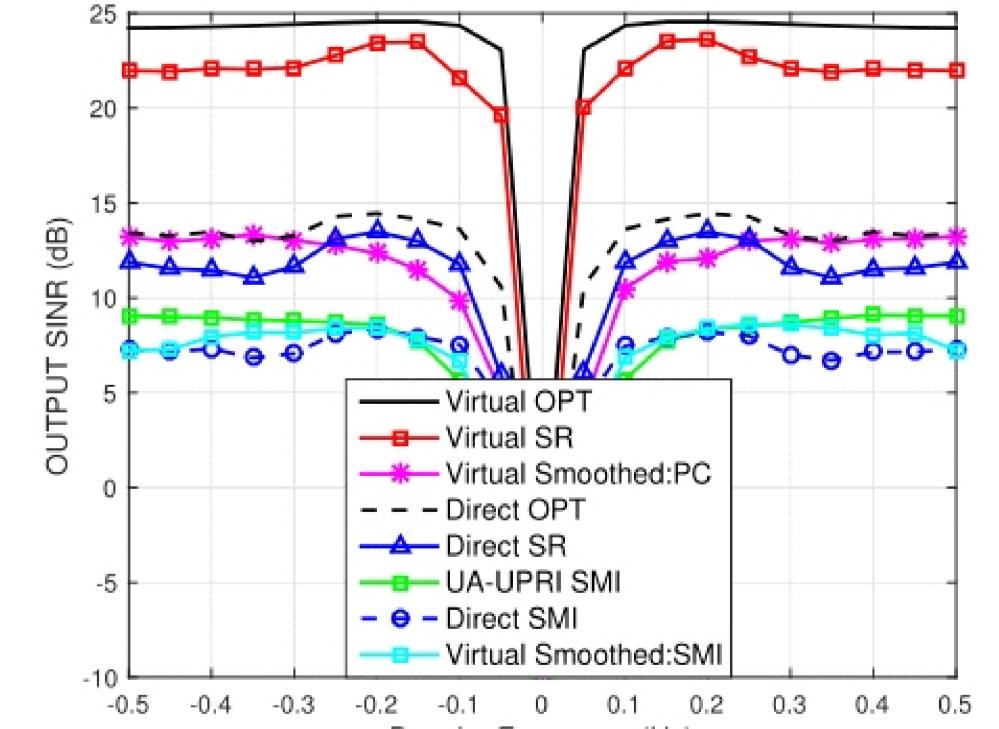
SINR versus the number of snapshots

Fast convergence and best performance

Note: target located at distance of 32km with normalized Doppler frequency of 0.3 and signal-to-noise (SNR) ratio of 0dB.

SINR versus different Doppler frequency

Show better SINR performance compared with others.

Note: achieves the theoretical performance with only 60 snapshots.

Note: the number of snapshots is 45

Conclusions

- A sparsity-based STAP algorithm by using the spatial-temporal sparsity of clutter in virtual domain was proposed.

- The proposed algorithm utilized more number of DoFs offered by the virtual snapshot than the spatial-temporal smoothing-based STAP.

- The proposed algorithm exhibited very fast convergence.

- The analysis of errors of virtual construction by using finite snapshots was conducted for setting the parameters of the sparse recovery algorithm.