CLUTTER SUPPRESSIUON VIA SPARSE SPACE-TIME SIGNAL RECOVERY

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Abstract- This paper presents a novel algorithm for space-time adaptive processing (STAP), by exploiting the characteristic of sparsity in the radar echo in Spatial-Doppler domain. Unlike traditional algorithm for STAP, our new method needs much less (even only one) training cells to eliminate the clutter energy in the test cell and reveal the target buried in strong clutter clearly. Owing to its excellent properties such as super-resolution and ultra-low sidelobe, our algorithm can effectively suppress the clutter and improve the performance for detecting moving target of radar on maneuvering platform.

1. INTRODUCTION

For space borne/airborne radar, STAP is an effective tool to reveal moving targets from strong ground clutter. It is common for traditional STAP methods to build the clutter suppression filter based on estimation of clutter covariance matrix using data from training cells [1]. To guarantee the performance of filter, 2*MN* independent and identically distributed (IID) training range cells are required, where N and M denote the numbers of the spatial channel and the azimuth pulse respectively [5]. However, clutter is statistically non-stationary and there exist only few IID range cells in actual heterogeneous environment. This implies that the traditional STAP is not suitable for being used for heterogeneous clutter suppression. To solve this problem, the clutter suppressing algorithm based on sparse space-time signal recovery is proposed in this paper. We will show that, by using ℓ_1 norm minimization algorithm [2], clutter energy distributed sparsely in the Spatial-Doppler plane could be estimated accurately with only ONE training cell. Then the clutter on test cell could be suppressed and moving target could be revealed clearly. Finally, numerical result with real data is given to demonstrate the performance of proposed algorithm.

2. FILTER DESIGN BASED ON SPARSE RECOVERY

Assume there is only one target, the data snapshots $\mathbf{x} \in \mathrm{C}^{NM}$ in test cell and in training cell can be written as

$$\mathbf{x} = \sum_{i=1}^{Q_c} \gamma_i \cdot \mathbf{v}(f_{s,i}, f_{d,i}) + \alpha \cdot \mathbf{v}(f_{s,t}, f_{d,t}) \quad \text{(for test cell)} \quad \text{and} \quad x = \sum_{i=1}^{Q_c} \gamma_i v(f_{s,i}, f_{d,i}) \quad \text{(for training cell)} \tag{1}$$

respectively. where Q_c is the total number of the clutter bins on Spatial-Doppler plane; γ_i and α are the complex amplitudes of the clutter bins and possible moving target, respectively; $f_{s,i}$ and $f_{d,i}$ are the spatial and Doppler frequencies of the i th clutter bins, respectively; $f_{s,t}$ and $f_{d,t}$ are the spatial and Doppler frequencies of the moving target, respectively; $\mathbf{v}(f_s, f_d)$ denotes the spatial-temporal steering vector and can be expressed as

$$\mathbf{v}(f_s, f_d) = \left[1,\ \exp\left(j2\pi f_d\right), ..., \exp\left(j2\pi\left(M-1\right) f_d\right)\right]^T \otimes \left[1,\ \exp\left(j2\pi f_s\right), ..., \exp\left(j2\pi\left(N-1\right) f_s\right)\right]^T, \tag{2}$$

where $\otimes$ denotes the Kronecker product. For the nature of the ground clutter, most of clutter energy concentrates on a small region of Spatial-Temporal plane (such as diagonal area). It implies the intrinsic sparsity of clutter echo.

Suppose Ψ is the $MN \times KL$ matrix as follows

$$\Psi = \left[\mathbf{v}\left(f_s^{(0)}, f_d^{(0)}\right), \cdots, \mathbf{v}\left(f_s^{(k)}, f_d^{(l)}\right), \cdots, \mathbf{v}\left(f_s^{(K-1)}, f_d^{(L-1)}\right)\right], \quad k = 0,1,...,K-1\,,\ \ l = 0,1,...,L-1 \tag{3}$$

where K is the number of the spatial frequency bin, L is the number of the Doppler frequency bin; $f_s^{(k)}$ denotes the kth spatial frequency bin and $f_d^{(l)}$ denotes the lth Doppler frequency bin. The data snapshot of radar echo from training cell can be expressed as $\mathbf{x} = \Psi\boldsymbol{\theta}$, where $\boldsymbol{\theta}$ is the energy distribution of radar echo on Spatial-Doppler plane. Recent results in field of Compressive Sensing (CS) [2][3] provide an feasible approach for recovery of sparse signal. As to our problem, since the radar echo is sparse in Spatial-Doppler plane, its spatial-temporal energy distribution could be accurately recovered with overwhelming probability by ℓ_1 norm minimization as

$$\min\|\theta\|_1,\ s,t \quad \|\mathrm{x} - \Psi\theta\|_2 \le \varepsilon \tag{4}$$

Problem (4) can be solved efficiently with linear programming or greedy algorithm [3]. The result $\boldsymbol{\theta}$ was used to estimate the covariance matrix

$$\hat{R}_{CS} = \sum_{i=1}^{Q_c} |\theta_i|^2 v(f_{s,i}, f_{d,i}) v^H(f_{s,i}, f_{d,i}) \tag{5}$$

With $\hat{R}_{CS}$ instead of ordinary estimation of covariance matrix directly using original data, various schemes of adaptive filter design, such as SMI and subspace projection, can be adopted to calculate the filter coefficient.

3. NUMERICAL RESULT AND CONCLUSIONS

Numerical results presented in this section were derived from processing publicly available real data collected by the DARPA sponsored Mountain Top program [6]. In Fig.1, the output of the filter based on CS technique (CS filter) and traditional SMI filter at the range cells for which data is available is shown. The covariance matrix for SMI filter was estimated using data snapshots from 80 range cells, not including the 5 samples around the target range. Meanwhile, CS filter only used data snapshot from single range cell. Two points are evident from the figure. Firstly, clutter is removed much more completely when CS filter is utilized. This benefit from the characteristic of super-resolution and ultra-low sidelobe of CS filter. Secondly, the performance of detection of CS filter is comparable to that of traditional SMI filter. It must be emphasized that this is achieved by CS filter using only ONE training snapshot. So it is a more suitable choice when clutter is non-stationary because it could uncover the essential Spatial-Doppler feature of clutter with very few training data. The numerical result shows great potential of filter based on CS technique to be applied in STAP, especially in heterogeneous clutter environments.

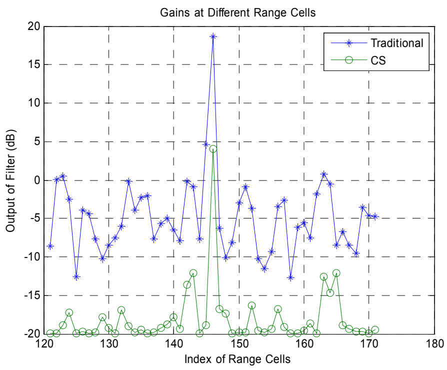

Fig.1 Gains of different range cells

4. REFERENCES

[1] J. R. Guerci, Space-Time Adaptive Processing for Radar. Norwood, MA: Artech House, 2003.

[2] D. Donoho, “Compressed sensing,” IEEE Trans. Inform. Theory, vol. 52, no. 4, pp. 1289–1306, Apr.2006.

[3] E. Candès, J. Romberg, and T. Tao, “Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information,” IEEE Trans. Inform. Theory, vol. 52, no. 2, pp. 489–509, Feb. 2006.

[4] R. Baraniuk and P. Steeghs, “Compressive radar imaging,” IEEE Radar Conference, pp. 128-133, April 2007.

[5] M. C. Wicks, M. Rangaswamy, R. Adve, and T. B. Hale, “Space-time adaptive processing,” IEEE Signal Processing Magazine, vol. 23, pp. 51—65, 2006.

[6] http://spib.rice.edu/spib/