

## **Radar Imaging With Quantized Measurements Based on**

## **Compressed Sensing**

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### **Motivation**

High-resolution radar imaging requires high-rate analog-to-digital converter (ADC), but

- the dynamic range of ADC degrades as a function of the sampling rate, and
- the large volumes of data produced by high-rate ADC raise the

**Basic Radar Observation Model** U  $\equiv$ S *e* measurement matrix target reflectivity additive noise received radar data Complex-valued vectors or matrices

 $\mathcal{R}\left\{\cdot\right\}$  - real part operator  $\mathcal{I}\left\{\cdot\right\}$  - imaginary part operator

burden of storing and transmission devices.

#### **Radar Imaging With Low-bit Quantized Data**

Advantage Enable high-rate ADC; Reduce the amount of data for storage and transmission.

#### Disadvantage

Large quantization error; Reduce the dynamic range of radar image.

One possible solution: Quantized Compressed Sensing (QCS)

## **QCS** Radar Imaging

**Classic CS Radar Imaging Objective:** reconstruct *x* from y = Ax + n**Method**:  $l_1$ -regularization

min  $\frac{1}{2} \|Ax - y\|_{2}^{2} + \lambda \sum_{i=N}^{N} [x_{i}^{2} + x_{i+N}^{2}]^{1/2}$ 

$$\mathbf{y} = \begin{bmatrix} \mathcal{R}\{\mathbf{s}\} \\ \mathcal{I}\{\mathbf{s}\} \end{bmatrix}, \ \mathbf{A} = \begin{bmatrix} \mathcal{R}\{\mathbf{U}\} & -\mathcal{I}\{\mathbf{U}\} \\ \mathcal{I}\{\mathbf{U}\} & \mathcal{R}\{\mathbf{U}\} \end{bmatrix}, \ \mathbf{x} = \begin{bmatrix} \mathcal{R}\{\mathbf{f}\} \\ \mathcal{I}\{\mathbf{f}\} \end{bmatrix}, \ \mathbf{n} = \begin{bmatrix} \mathcal{R}\{\mathbf{e}\} \\ \mathcal{I}\{\mathbf{e}\} \end{bmatrix}$$

y = Ax + nReal-valued vectors or matrices

Let *Q* denote the quantizer function:

1-bit ( $\square$ : false targets)

 $\boldsymbol{q} = Q(\boldsymbol{A}\boldsymbol{x} + \boldsymbol{n})$ 

Let *l* and *u* denote the lower and upper thresholds associated with q, respectively.

 $l \leq Ax + n \leq u$ 

Simulation

# i=1**QCS Radar Imaging Objective:** reconstruct *x* from $l \leq Ax + n \leq u$ Method: maximum *a posteriori* (MAP) estimation $\min -\ln p(\boldsymbol{q}|\boldsymbol{x}) - \ln p(\boldsymbol{x})$ **Two assumptions:** $n_i$ are iid Gaussian random variables $p(\boldsymbol{q}|\boldsymbol{x}) = \prod_{i=1}^{2M} \left| \Phi\left(\frac{-\boldsymbol{a}_i^T \boldsymbol{x} + \boldsymbol{u}_i}{\sigma}\right) - \Phi\left(\frac{-\boldsymbol{a}_i^T \boldsymbol{x} + \boldsymbol{l}_i}{\sigma}\right) \right|$ $\Phi$ is the cumulative distribution function (CDF) of the standard normal distribution.

The target reflectivity vector is sparse. The  $l_1$ -norm can be used to enforce the sparsity.



$$-\ln p(\mathbf{x}) \propto \left\| \mathbf{f} \right\|_{1} = \sum_{i=1}^{N} \sqrt{\mathbf{x}_{i}^{2} + \mathbf{x}_{i+N}^{2}}$$

 $\min - \sum \ln |\Phi|$ 

a convex, unconstrained optimization problem

 $\left(\frac{-\boldsymbol{a}_{i}^{T}\boldsymbol{x}+\boldsymbol{u}_{i}}{\sigma}\right)-\Phi\left(\frac{-\boldsymbol{a}_{i}^{T}\boldsymbol{x}+\boldsymbol{l}_{i}}{\sigma}\right)\left|+\lambda\sum_{i=1}^{N}\sqrt{\boldsymbol{x}_{i}^{2}+\boldsymbol{x}_{i+N}^{2}}\right|$ 



For coarsely quantized data like 1-bit and 2-bti quantization, the proposed method outperforms  $l_1$ -regularization. For high-resolution quantization,

$$-\ln p(\boldsymbol{q}|\boldsymbol{x}) \approx \frac{1}{2} \|\boldsymbol{A}\boldsymbol{x} - \boldsymbol{y}\|_{2}^{2} + \text{Constant}$$

Thus the proposed method and  $l_1$ -regularization are approximately equivalent.