

University of L'Aquila (Italy) Electrical Engineering Faculty





CoSeRa Bonn 2013

Tomographic SAR Inversion by The Generic Log-Barrier Algorithm the Second Order Cone Programming Approach.



Prof. Nazzareno PIERDICCA (University La Sapienza) Prof. Piero CIOTTI (University of L'Aquila) Dr. Filippo BIONDI (Italian Ministry Of Defence)

LIST OF ARGUMENTS

- Tomographic SAR analysis by spectral estimators;
- Under-sampled Tomographic SAR data-sets;
- Validation of Compressed Sensing (CS) signal processing for mixed environment by the Second Order Cone Programming (SOCP).

² F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach

Multi-Baseline Geometry AcquisitionSAR Tomography;







- Statistical De-correlation Effects in Repeat-Pass Tom-SAR acquisition Campaign;
 - **3** F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach

MB-PolInSAR Environments



[1] Yue Huang, Laurent Ferro-Famil, Fabrizio Lombardini: Improved Tomographic SAR Focusing using Automatic Baseline Error Compensation, ESA PolInSAR 2012.

Tomographic Problem Solution

- y=A*x
- y= Known Observation Parameter;
- A=Geometric Built, Steering Matrix;
- x=Unknown reflectivity function, (vertical reflectivity profile);

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_P \end{bmatrix} \text{ with} A = \begin{bmatrix} a_{11} & a_{21} & \cdots & a_{1N} \\ a_{12} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{P1} & a_{P2} & \cdots & a_{PN} \end{bmatrix} A_{i,k} = e^{-j\frac{4\pi}{\lambda}r_{i,k}}$$
$$y \in \mathbb{C}^{\mathsf{P}}_{\mathsf{NN}}$$
$$y = \mathsf{Ax} \qquad A \in \mathbb{C}^{\mathsf{PXN}}_{\mathsf{NN}}$$



6 F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach

Tomographic Problem Solution



- A is not directly invertible, P<N
- Direct Method: $A^{-1} = A^{\dagger}$
- Indirect Method, (Covariance Matrix Estimation);
- This leads to poor results for many practical applications
- F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order 7 **Cone Programming Approach**

Covariance Matrix Estimation
Tomographic Processing Procedure: Covariance Matrix Estimation;

$$\mathbf{R} = \frac{1}{L} \sum_{j=1}^{L} \mathbf{b}(j) \ \mathbf{b}^{\dagger}(j)$$

$$L = \text{Number of independent Looks}$$
Covariance Matrix Estimation
$$\mathbf{R}_{k} = \begin{bmatrix} \gamma_{k}(1,1) & \gamma_{k}(1,2) & \cdots & \gamma_{k}(1,\mathbf{P}) \\ \gamma_{k}(2,1) & \gamma_{k}(2,2) & & \gamma_{k}(2,\mathbf{P}) \\ \vdots & & \ddots & \vdots \\ \gamma_{k}(\mathbf{P},1) & \gamma_{k}(\mathbf{P},2) & \cdots & \gamma_{k}(\mathbf{P},\mathbf{P}) \end{bmatrix}$$

$$\mathbf{k} = 1.....\text{Range Length}$$

$$\mathbf{P} = \text{Observation Stack length}$$

.

Beamforming:
$$\hat{\mathbf{x}} = \operatorname{argmax} \left[a^{\dagger} \mathbf{R} a \right];$$

Capon: $\hat{\mathbf{x}} = \operatorname{argmax} \left\{ \frac{1}{a^{\dagger} \mathbf{R}^{-1} a} \right\};$

Compressed Sensing

An Optimization Problem seeks to find the best solution so that is true:



Inequality Constrained Problem minimize $f_0(x)$ subject to $f_i(x) \leq 0$ and y = Ax $x = (x_1 \dots x_N)$ optimization variable $f_0: \mathbb{C}^N \to \mathbb{C}$ objective function $f_i: \mathbb{C}^N \to \mathbb{C}; i=1...m$ constraint functions

 $f_0, \dots, f_m :\in \mathbb{C}^n \to \mathbb{C}$ are convex and twice continuously differentiable

 $A \in \mathbb{C}^{P \times N}$ with **Rank** A=P<N continuously differentiable

 $\hat{x}, f(\hat{x}) = \hat{p}$ is the optimal solition



 $\exists D \text{ s.t. } y = Ax \text{ and } f_i(x) \leq 0; i = 1 \cdots m.s.t.$

Duality: Karush-Kuhn-Tucker(*KKT*) Condition:

any optimization problem with differentiable objective and constraint functions for which strong duality obtains, any pair of primal and dual optimal points must satisfy the following $\exists \lambda^* \in \mathbb{C}^m$. $v \in \mathbb{C}^P$ s.t. $Ax^* = y, f_i(x^*) \le 0; i = 1, \dots, m$ $\lambda^* > 0$ $\nabla f_0(x^*) + \sum \lambda_i \nabla f_i(x^*) + A^T v^* = 0$ $\lambda_{i}^{*}f_{i}(x^{*})=0; i=1\cdots m$

Interior Point Methods Applying Newton Methods Inequality Constrained Problem Quality Constrained Problem

Use of Log-Barrier Method

The Log-Barrier Algorithm for SOCP

The best Equality Constrained Problem is: minimize $f_0(x) + \sum I_i(f_i(x))$ subject to y = Axwhere $I_: \mathbb{R} \to \mathbb{R}$ has the following indicator function for the non-positive reals



$$I_{-} = \begin{bmatrix} 0; u \leq 0 \\ \infty; u > 0 \end{bmatrix}$$

No Inequality Constraint But is not differentiable

CVX – Convex Optimization The Log-Barrier Algorithm for SOCP

 $I_{\rm I}$ is approximated into: $\hat{I}_{\rm I}$ $\hat{I}_{-} = -(1/t)\log(-u)$ minimize $f_0(x) + \sum \left[-(1/t) \log (-f_i(x)) \right]$ subject to y = Axfor the non-positive reals $\phi = [-(1/t)\log(-f_i(x))]$ The Log-Barrier is twice differentiable -2

5

CVX – Convex Optimization The Log-Barrier function is twice differentiable

$$g_{x} = \nabla \phi(x) = \sum_{i=1}^{m} \frac{1}{-f_{i}(x)} \nabla f_{i}(x)$$
$$H_{x} = \nabla^{2} \phi = \frac{1}{\tau} \sum_{i=1}^{m} \frac{1}{f_{i}(x)^{2}} \nabla f_{i}(x)^{T} + \sum_{i=1}^{m} \frac{1}{-f_{i}(x)^{2}} \nabla^{2} f_{i}(x)$$

Approximation of the Log-Barrier Problem

$$f_0(x+\Delta x) \approx x + \langle g_x | \Delta_x \rangle + \frac{1}{2} \langle H_x \Delta_x | \Delta_x \rangle = q(x+\Delta x)$$

Solution: find Δ_x that minimizes $q(x + \Delta_x)$ subject to Ax=y *is the solution of the following linear equiation set* :

$$\tau \begin{vmatrix} H_x & A_0^T \\ A_0 & 0 \end{vmatrix} \begin{vmatrix} \Delta_x \\ v \end{vmatrix} = -\tau g_x$$

- We have used a "matrix free" solver such as Conjugate Gradients (C.G.)
- The following two algorithms results has been opposed:
- Min-I1 with bounded residual correlation (Dantzig Selector) LP;

 $min \|x\|_1$ subject to $\|A^*(Ax-y)\|_{\infty} \leq \gamma$

Min-I1 with quadratic constraints SOCP

 $\min \|x\|_1$ subject to $\|(Ax-y)\|_2 \leq \epsilon$



18 F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach

CVX – Convex Optimization Validation of the Log-Barrier algorithm to L1





CVX – Convex Optimization Distributed Scatterer - Case (a)



CVX – Convex Optimization Distributed Scatterer - Case (b)





• Distributed Scatterer Case (c)



CVX – Convex Optimization Realistic PolSARPro Vegetation Environment P-band L-band



24 F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach





25 F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach



Capon Filter: Two layer definition SOCP: Three layer definition

Airborne Real Data-Set

- Mission: TROPISAR-2009 (SETHI ONERA ESA)
- Geometry:
- 6 Tracks;
- Full POL;
- P and L-Band;
- Vertical Baseline 50 ft;
- Height 4000m.



²⁷ F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach

Real data P-band

optical

radar





•Blue line case Tomogram

Pauli-RGB







29 F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach

•Red line case Tomogram









A great resolution improvement is observed





32 F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach

CVX – Convex Optimization optical

radar





34 F. Biondi, P. Ciotti, N. Pierdicca. Tomographic SAR Inversion by the Generic Log-Barrier Algorithm, The Second Order Cone Programming Approach







37

•The Resolution is doubled



Conclusions

- Demonstration that Convex Optimization can be successfully used for SAR Tomography;
- L1 Norm minimization with quadratic constraints where a Log-Barrier algorithm with Newton iteration was implemented;
- Good resolution improvement has been observed.

Future Work

- Efficient Tomographic reconstruction based on the Total Variational (TV) minimization of estimated image;
- TV may have higher computational speed respect to Classical CS.



THANKS FOR YOUR ATTENTION