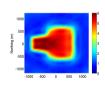
Compressive Conjugate Directions: Linear Theory

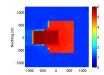
A new tool for sparsity-promoting optimization

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Motivation: regularized large-scale optimization



- Model styling=regularization is critical in applications
- Non-smooth sparsity/blockiness-promoting L_1/TV regularization
- Computationally expensive algorithms exist
- Goal: a computationally feasible and accurate algorithm

Problem: L_1/TV -regularized linear LS fitting



$$\|\mathbf{B}\mathbf{u}\|_1 + \frac{\alpha}{2}\|\mathbf{A}\mathbf{u} - \mathbf{d}\|_2^2 \rightarrow \min,$$
 (1)

$$\mathbf{B} = \mathbf{I} \tag{2}$$

or

$$\mathbf{B} = \nabla. \tag{3}$$

A good algorithm: ADMM/ "Split Bregman" (Glowinski, Maroco)



ADMM requires solving lots of large LS problems in a loop:

$$\mathbf{u}_{k+1} = \operatorname{argmin} \frac{\alpha}{2} \|\mathbf{A}\mathbf{u} - \mathbf{d}\|_{2}^{2} + \frac{\lambda}{2} \|\mathbf{z}_{k} - \mathbf{B}\mathbf{u} + \mathbf{b}_{k}\|_{2}^{2}, \text{ very hard!}$$

$$\mathbf{z}_{k+1} = \operatorname{argmin} \|\mathbf{z}\|_{1} + \frac{\lambda}{2} \|\mathbf{z} - \mathbf{B}\mathbf{u}_{k+1} + \mathbf{b}_{k}\|_{2}^{2}, \quad \text{easy}$$

$$\mathbf{b}_{k+1} = \mathbf{b}_{k} + \mathbf{z}_{k+1} - \mathbf{B}\mathbf{u}_{k+1}, \ k = 0, 1, 2, \dots \quad \text{trivial}$$

ISTA/FISTA (Beck & Teboulle)—shorten the inner loop



FISTA speeds up gradient descent using Nesterov relaxation:

$$\mathbf{y}_{k+1} = \mathbf{u}_{k} - \gamma \alpha \mathbf{A}^{T} \left(\mathbf{A} \mathbf{u}_{k} - \mathbf{d} \right), \quad \Leftarrow \text{ single iteration!}$$

$$\mathbf{z}_{k+1} = \text{shrink} \left\{ \mathbf{y}_{k+1}, \gamma \right\}, \quad \Leftarrow \text{ trivial}$$

$$\zeta_{k+1} = \left(1 + \sqrt{1 + 4\zeta_{k}^{2}} \right) / 2, \quad \Leftarrow \text{ trivial}$$

$$\mathbf{u}_{k+1} = \mathbf{y}_{k+1} + \frac{\zeta_{k} - 1}{\zeta_{k+1}} \left(\mathbf{y}_{k+1} - \mathbf{y}_{k} \right), \Leftarrow \text{ trivial}$$
(5)

Hot-restarted Conjugate Gradients (RCG)



Restarted CG does a few CG iterations of each LS problem:

$$\mathbf{u}_{k+1} = N \text{ iters of } \operatorname{argmin} \frac{\alpha}{2} \|\mathbf{A}\mathbf{u} - \mathbf{d}\|_{2}^{2} + \frac{\lambda}{2} \|\mathbf{z}_{k} - \mathbf{B}\mathbf{u} + \mathbf{b}_{k}\|_{2}^{2},$$

$$\mathbf{z}_{k+1} = \operatorname{argmin} \|\mathbf{z}\|_{1} + \frac{\lambda}{2} \|\mathbf{z} - \mathbf{B}\mathbf{u}_{k+1} + \mathbf{b}_{k}\|_{2}^{2},$$

$$\mathbf{b}_{k+1} = \mathbf{b}_{k} + \mathbf{z}_{k+1} - \mathbf{B}\mathbf{u}_{k+1}, \ k = 0, 1, 2, \dots$$
(6)

Compressive Conjugate Directions



- **Problem**: rhs change⇒previous geometry information of standard CG residuals is lost
- Observation: the quadratic shape of the objective function (6) does not change
- Idea: store the previous conjugate directions GMRES-style

Compressive Conjugate Directions



1:
$$\mathbf{u}_{0} \leftarrow \mathbf{0}^{N}$$
, $\mathbf{z}_{0} \leftarrow \mathbf{0}^{K}$; $\mathbf{b}_{0} \leftarrow \mathbf{0}^{K}$, $\mathbf{v}_{0} \leftarrow \begin{bmatrix} \sqrt{\alpha}\mathbf{d}; \sqrt{\lambda} (\mathbf{z}_{0} + \mathbf{b}_{0}) \end{bmatrix}$

2: $\mathbf{F} \leftarrow [\mathbf{A}; \mathbf{B}]$, $\mathbf{p}_{0} \leftarrow \mathbf{F}^{T}\mathbf{v}_{0}$, $\mathbf{q}_{0} \leftarrow \mathbf{F}\mathbf{p}_{0}$, $\delta_{0} \leftarrow \mathbf{q}_{0}^{T}\mathbf{q}_{0}$

3: $\mathbf{for} \ k = 0, 1, 2, 3, \dots \mathbf{do}$

4: $\tau_{i} \leftarrow \mathbf{q}_{i}^{T}\mathbf{v}_{k}/\delta_{i}$, $i = 0, 1, \dots, k$, $\mathbf{u}_{k+1} \leftarrow \sum_{i=0}^{k} \tau_{i}\mathbf{p}_{i}$

5: $\mathbf{z}_{k+1} \leftarrow \text{shrink} \{\mathbf{B}\mathbf{u}_{k+1} - \mathbf{b}_{k}, 1/\lambda\}$

6: $\mathbf{b}_{k+1} \leftarrow \mathbf{b}_{k} + \mathbf{z}_{k+1} - \mathbf{B}\mathbf{u}_{k+1}$

7: $\mathbf{v}_{k+1} \leftarrow \begin{bmatrix} \sqrt{\alpha}\mathbf{d}; \sqrt{\lambda} (\mathbf{z}_{k+1} + \mathbf{b}_{k+1}) \end{bmatrix}$

8: $\mathbf{r}_{k+1} \leftarrow \mathbf{v}_{k+1} - \sum_{i=0}^{k} \tau_{i}\mathbf{q}_{i}$

9: $\mathbf{w}_{k+1} \leftarrow \mathbf{F}^{T}\mathbf{r}_{k+1}$, $\mathbf{s}_{k+1} \leftarrow \mathbf{F}\mathbf{w}_{k+1}$

10: $\beta_{i} \leftarrow -\mathbf{q}_{i}^{T}\mathbf{s}_{k+1}/\delta_{i}$, $i = 0, 1, \dots, k$

11: $\mathbf{p}_{k+1} \leftarrow \sum_{i=0}^{k} \beta_{i}\mathbf{p}_{i} + \mathbf{w}_{k+1}$, $\mathbf{q}_{k+1} \leftarrow \sum_{i=0}^{k} \beta_{i}\mathbf{q}_{i} + \mathbf{s}_{k+1}$

12: $\delta_{k+1} \leftarrow \mathbf{q}_{k+1}^{T}\mathbf{q}_{k+1}$

13: if $\delta_{k+1} = 0$, $\delta_{k+1} \leftarrow 1$, $\mathbf{p}_{k+1} \leftarrow \mathbf{0}^{N}$, $\mathbf{q}_{k+1} \leftarrow \mathbf{0}^{M+K}$

14: Exit loop if $\|\mathbf{u}_{k+1} - \mathbf{u}_{k}\|_{2}/\|\mathbf{u}_{k}\|_{2} \leq \text{target accuracy}$

15: end for

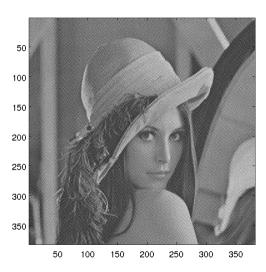
A denoising example (A = I). True image





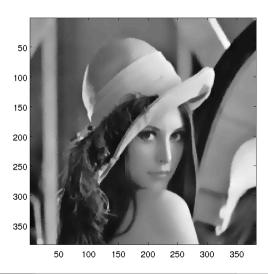
Noisy image





RCG denoising





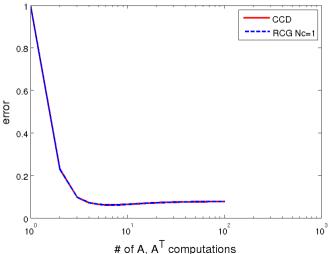
CCD denoising





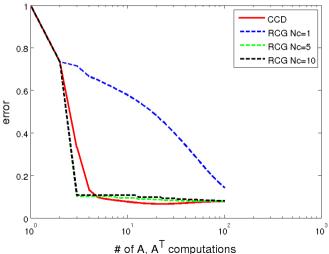


Normalized ||true-inverted||₂; $\kappa(LS)=1.8$



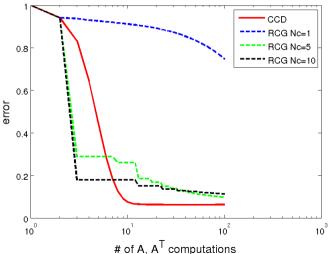






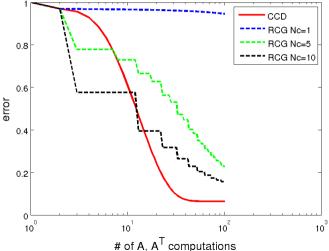








Normalized $||\text{true-inverted}||_2$; $\kappa(LS)=8001$





Surface deformation due to distributed dilatational (e.g. pressure) sources:

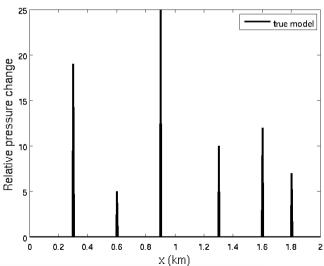
$$\mathbf{Au} = d(x,y),$$

$$d(x,y) = c \int_0^A \int_0^A \frac{Du(\xi,\eta)d\xi d\eta}{(D^2 + (x-\xi)^2 + (y-\eta)^2)^{3/2}},$$
(7)

Ill-conditioned inverse problem of resolving pressure from surface deformation...

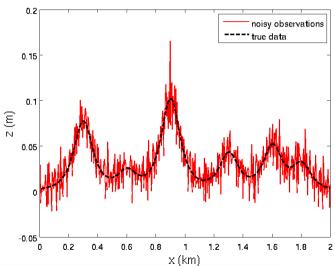
True spiky pressure model





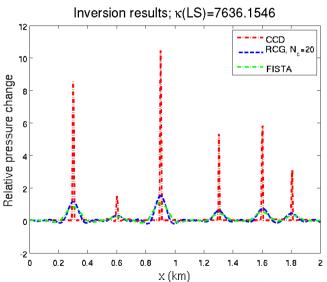
Noisy data





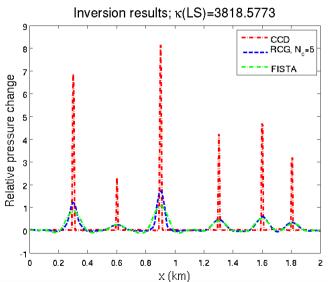
$\lambda = .05$, 100 iterations





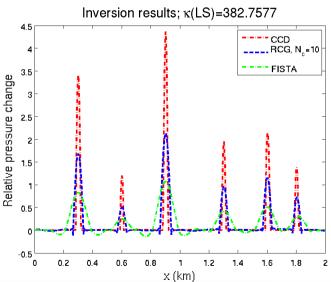
$\lambda = .1$, 100 iterations





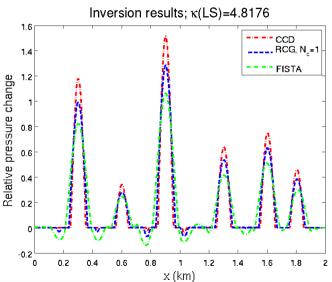
$\lambda = 1$, 100 iterations





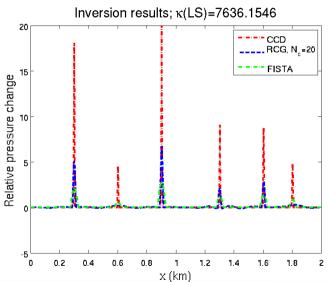
$\lambda = 100$, 1000 iterations





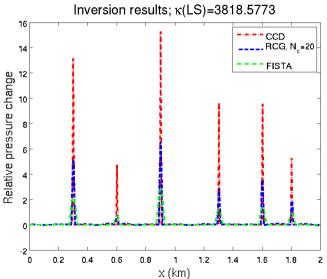
$\lambda = .05$, 1000 iterations





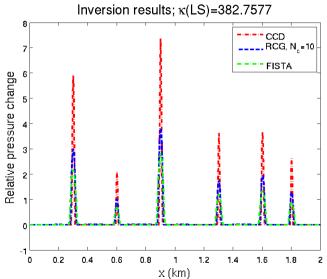
$\lambda = .1$, 1000 iterations





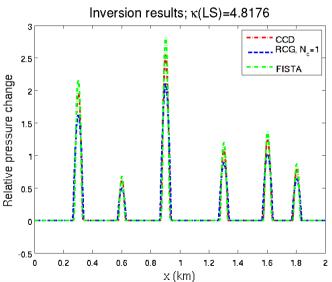
$\lambda = 1$, 1000 iterations





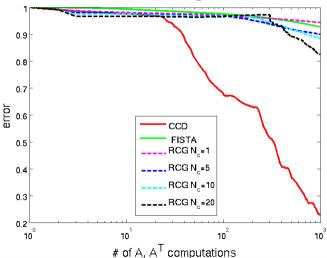
$\lambda = 100$, 1000 iterations





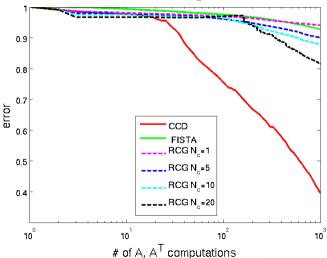






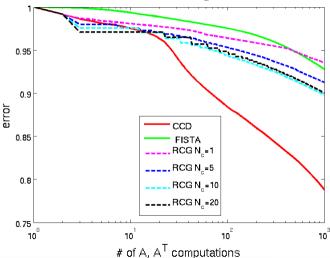






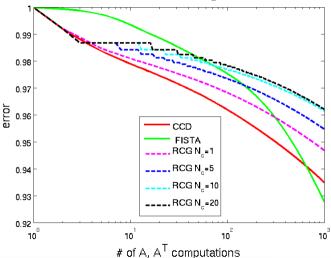








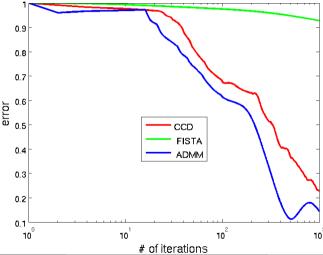




$\lambda = .05$, comparison with ADMM and exact solver



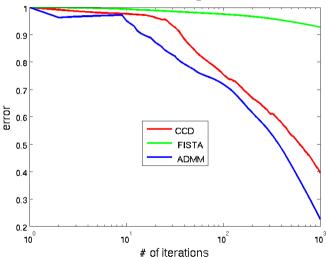




$\lambda = .1$, comparison with ADMM and exact solver

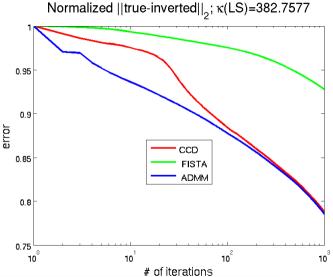






$\lambda = 1$, comparison with ADMM and exact solver

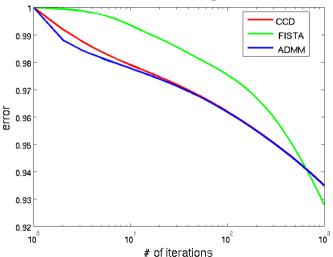




$\lambda = 100$, comparison with ADMM and exact solver

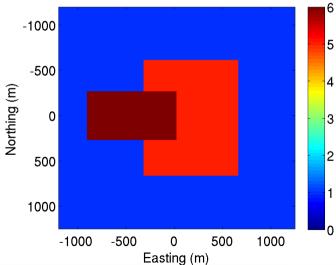






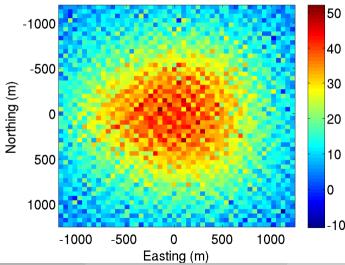
True blocky pressure model





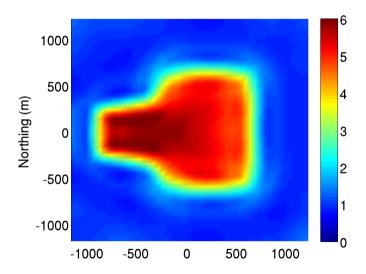
Noisy surface uplift data





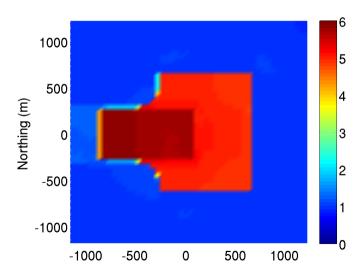
$\lambda = 10$, 100 iterations of RCG





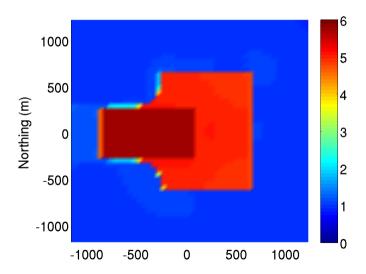
$\lambda = 10$, 100 iterations of CCD





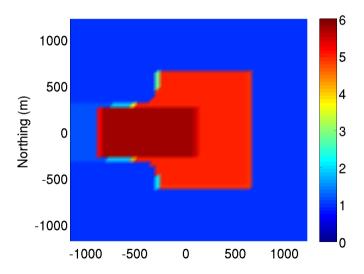
$\lambda = 10$, 1000 iterations of RCG





$\lambda = 10$, 1000 iterations of CCD

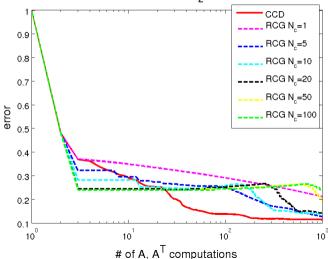




$\lambda = 5$, convergence comparison



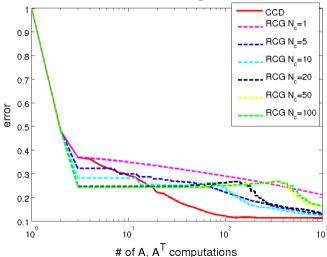




$\lambda = 10$, convergence comparison



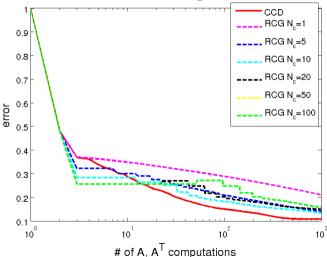




$\lambda = 50$, convergence comparison







Conclusions and perspectives



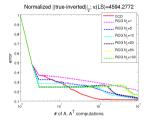
- 1. Adresses a **nasty** trade-off of classic methods: in practical problems **good** condition numbers of intermediate LS⇔**slow** ADMM convergence (Glowinski, 1982)
- 2. CCD beats alternatives when the intermediate LS is ill-conditioned!
- 3. Trades applications of the modeling operator for increased memory usage
- 4. A fast nonlinear extension has been developed and can be used with FWI
- 5. What's the expected ADMM convergence vs worst case?

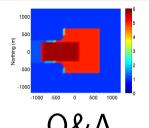
Acknowledgements

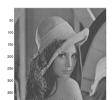


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100 150