Accelerating image recovery using variable splitting methods

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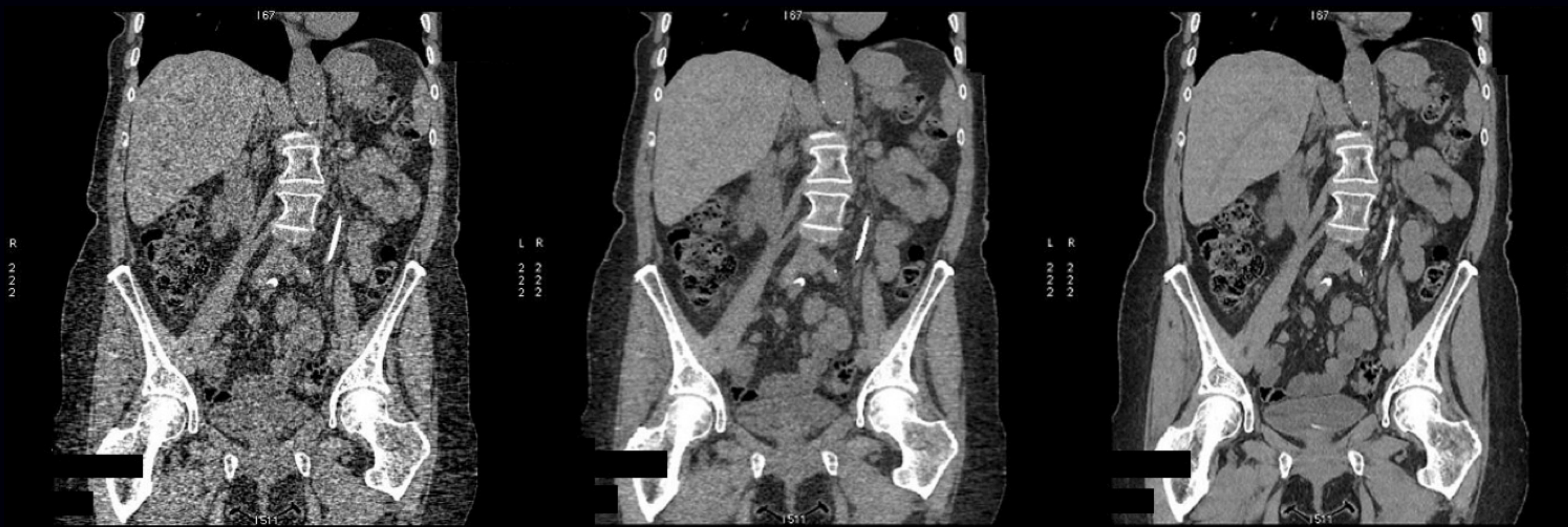
Statistical image reconstruction: a CT revolution

- A picture is worth 1000 words
- (and perhaps several 1000 seconds of computation?)



Thin-slice FBP	ASIR	Statistical
Seconds	A bit longer	Much longer

(Same sinogram, so all at same dose)

Outline

- Image denoising (review)

- Image restoration
  Antonios Matakos, Sathish Ramani, JF, IEEE T-IP 2013 (To appear)
  Accelerated edge-preserving image restoration without boundary artifacts

- Low-dose X-ray CT image reconstruction
  Sathish Ramani & JF, IEEE T-MI, Mar. 2012
  A splitting-based iterative algorithm for accelerated statistical X-ray CT reconstruction

- Model-based MR image reconstruction
  Sathish Ramani & JF, IEEE T-MI, Mar. 2011
  Parallel MR image reconstruction using augmented Lagrangian methods

Image denoising

Denoising using sparsity

Measurement model:

$$\underbrace{\boldsymbol{y}}_{\text{observed}} = \underbrace{\boldsymbol{x}}_{\text{unknown}} + \underbrace{\boldsymbol{\varepsilon}}_{\text{noise}}$$

Object model: assume $\boldsymbol{Q}\boldsymbol{x}$ is sparse (compressible) for some orthogonal sparsifying transform $\boldsymbol{Q}$, such as an orthogonal wavelet transform (OWT).

Sparsity regularized estimator:

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \underbrace{\frac{1}{2}\|\boldsymbol{y}-\boldsymbol{x}\|_2^2}_{\text{data fit}} + \beta \underbrace{\|\boldsymbol{Q}\boldsymbol{x}\|_p}_{\text{sparsity}}.$$

Regularization parameter β determines trade-off.

Equivalently (because $\boldsymbol{Q}^{-1} = \boldsymbol{Q}'$ is an orthonormal matrix):

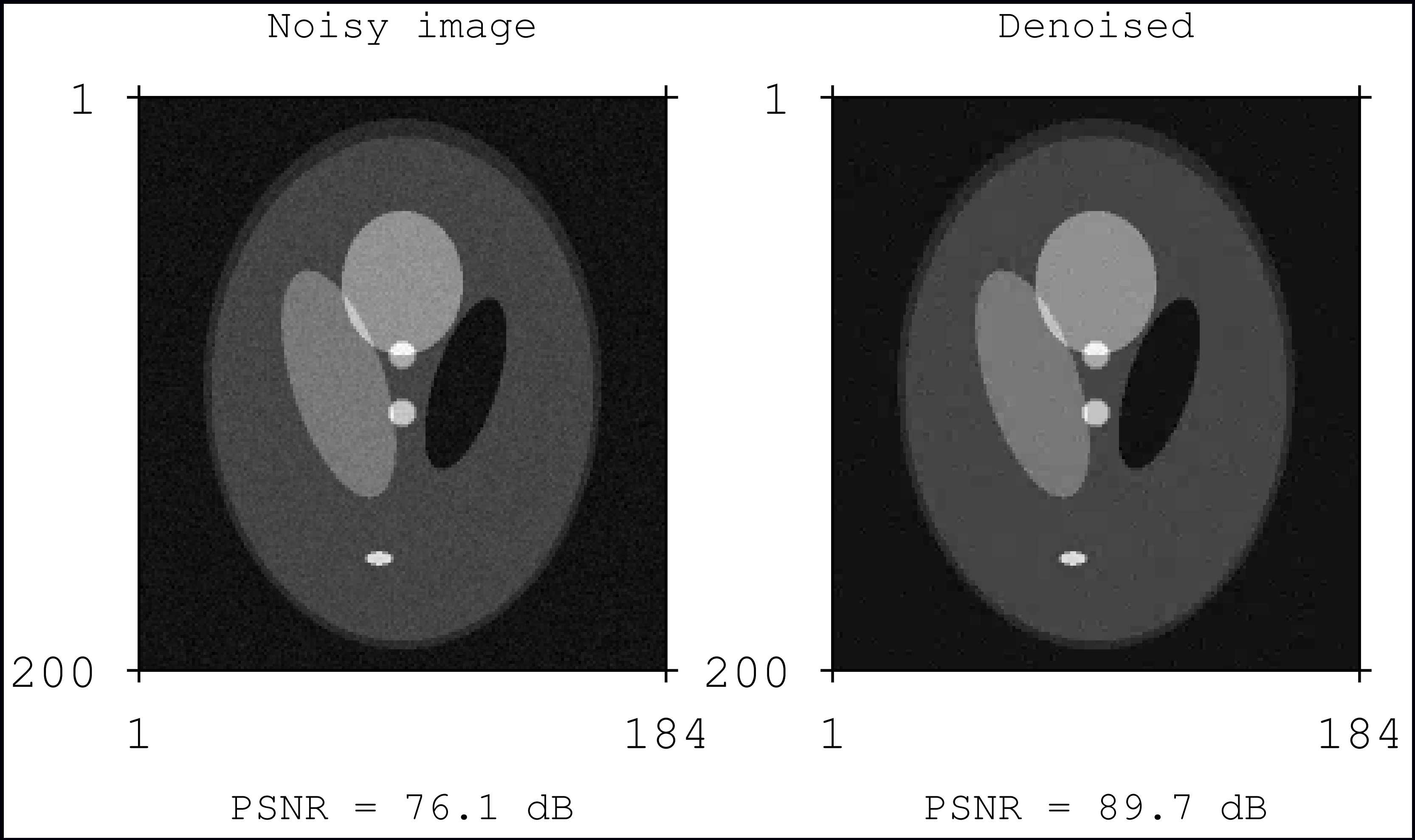
$$\hat{\boldsymbol{x}} = \boldsymbol{Q}'\hat{\boldsymbol{\theta}}, \quad \hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \frac{1}{2}\|\boldsymbol{Q}\boldsymbol{y}-\boldsymbol{\theta}\|_2^2 + \beta\|\boldsymbol{\theta}\|_p = \operatorname{shrink}(\boldsymbol{Q}\boldsymbol{y} : \beta, p)$$

Non-iterative solution!

But sparsity in orthogonal transforms often yields artifacts.

Spin cycling...

Hard thresholding example



$p = 0$, orthonormal Haar wavelets

Sparsity using shift-invariant models

Analysis form:
Assume $\boldsymbol{R}\boldsymbol{x}$ is sparse for some sparsifying transform $\boldsymbol{R}$.
Often $\boldsymbol{R}$ is a "tall" matrix, *e.g.*, finite differences along horizontal and vertical directions, *i.e.*, anisotropic total variation (TV).
Often $\boldsymbol{R}$ is shift invariant: $\|\boldsymbol{R}\boldsymbol{x}\|_p = \|\boldsymbol{R}\,\mathrm{circshift}(\boldsymbol{x})\|_p$ and $\boldsymbol{R}'\boldsymbol{R}$ is circulant.

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \frac{1}{2}\|\boldsymbol{y} - \boldsymbol{x}\|_2^2 + \beta \underbrace{\|\boldsymbol{R}\boldsymbol{x}\|_p}_{\text{transform sparsity}}.$$

Synthesis form
Assume $\boldsymbol{x} = \boldsymbol{S}\boldsymbol{\theta}$ where coefficient vector $\boldsymbol{\theta}$ is sparse.
Often $\boldsymbol{S}$ is a "fat" matrix (over-complete dictionary) and $\boldsymbol{S}'\boldsymbol{S}$ is circulant.

$$\hat{\boldsymbol{x}} = \boldsymbol{S}\hat{\boldsymbol{\theta}}, \quad \hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \frac{1}{2}\|\boldsymbol{y} - \boldsymbol{S}\boldsymbol{\theta}\|_2^2 + \beta \underbrace{\|\boldsymbol{\theta}\|_p}_{\text{sparse coefficients}}$$

Analysis form preferable to synthesis form?
(Elad *et al.*, Inv. Prob., June 2007)

Constrained optimization

Unconstrained estimator (analysis form for illustration):

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{x}\|_2^2 + \beta \|\boldsymbol{R}\boldsymbol{x}\|_p .$$

(Nonnegativity constraint or box constraints easily added.)

Equivalent constrained optimization problem:

$$\min_{\boldsymbol{x},\boldsymbol{v}} \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{x}\|_2^2 + \beta \|\boldsymbol{v}\|_p \text{ sub. to } \boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}.$$

(Y. Wang *et al.*, SIAM J. Im. Sci., 2008)
(M Afonso, J Bioucas-Dias, M Figueiredo, IEEE T-IP, Sep. 2010)

(The auxiliary variable $\boldsymbol{v}$ is discarded after optimization; keep only $\hat{\boldsymbol{x}}$.)

Penalty approach:

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \min_{\boldsymbol{v}} \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{x}\|_2^2 + \beta \|\boldsymbol{v}\|_p + \frac{\mu}{2} \|\boldsymbol{v} - \boldsymbol{R}\boldsymbol{x}\|_2^2 .$$

Large μ better enforces the constraint $\boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}$, but can worsen conditioning.

Preferable (?) approach: augmented Lagrangian.

Augmented Lagrangian method: V1

General linearly constrained optimization problem:

$$\min_{\boldsymbol{u}} \Psi(\boldsymbol{u}) \text{ sub. to } \boldsymbol{C}\boldsymbol{u} = \boldsymbol{b}.$$

Form *augmented Lagrangian*:

$$L(\boldsymbol{u}, \boldsymbol{\gamma}) \triangleq \Psi(\boldsymbol{u}) + \boldsymbol{\gamma}'(\boldsymbol{C}\boldsymbol{u} - \boldsymbol{b}) + \frac{\rho}{2}\|\boldsymbol{C}\boldsymbol{u} - \boldsymbol{b}\|_2^2$$

where $\boldsymbol{\gamma}$ is the *dual variable* or *Lagrange multiplier vector*.

AL method alternates between minimizing over $\boldsymbol{u}$ and gradient ascent on $\boldsymbol{\gamma}$:

$$\begin{aligned} \boldsymbol{u}^{(n+1)} &= \arg\min_{\boldsymbol{u}} L(\boldsymbol{u}, \boldsymbol{\gamma}^{(n)}) \\ \boldsymbol{\gamma}^{(n+1)} &= \boldsymbol{\gamma}^{(n)} + \rho\left(\boldsymbol{C}\boldsymbol{u}^{(n+1)} - \boldsymbol{b}\right). \end{aligned}$$

Desirable convergence properties.
AL penalty parameter ρ affects convergence *rate*, not solution!

Unfortunately, minimizing over $\boldsymbol{u}$ is impractical here:

$\boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}$ equivalent to $\boldsymbol{C}\boldsymbol{u} = \boldsymbol{b}, \quad \boldsymbol{C} = [\boldsymbol{R} \quad -\boldsymbol{I}], \quad \boldsymbol{u} = \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{v} \end{bmatrix}, \quad \boldsymbol{b} = \boldsymbol{0}.$

Augmented Lagrangian method: V2

General linearly constrained optimization problem:

$$\min_{\boldsymbol{u}} \Psi(\boldsymbol{u}) \text{ sub. to } \boldsymbol{C}\boldsymbol{u} = \boldsymbol{b}.$$

Form (modified) *augmented Lagrangian* by completing the square:

$$L(\boldsymbol{u}, \boldsymbol{\eta}) \triangleq \Psi(\boldsymbol{u}) + \frac{\rho}{2} \|\boldsymbol{C}\boldsymbol{u} - \boldsymbol{\eta}\|_2^2 + C_{\boldsymbol{\eta}},$$

where $\boldsymbol{\eta} \triangleq \boldsymbol{b} - \frac{1}{\rho}\boldsymbol{\gamma}$ is a modified *dual variable* or *Lagrange multiplier vector*.

AL method alternates between minimizing over $\boldsymbol{u}$ and gradient ascent on $\boldsymbol{\eta}$:

$$\begin{aligned} \boldsymbol{u}^{(n+1)} &= \arg\min_{\boldsymbol{u}} L(\boldsymbol{u}, \boldsymbol{\gamma}^{(n)}) \\ \boldsymbol{\eta}^{(n+1)} &= \boldsymbol{\eta}^{(n)} - (\boldsymbol{C}\boldsymbol{u}^{(n+1)} - \boldsymbol{b}). \end{aligned}$$

Desirable convergence properties.
AL penalty parameter ρ affects convergence *rate*, not solution!

Unfortunately, minimizing over $\boldsymbol{u}$ is impractical here:

$\boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}$ equivalent to $\boldsymbol{C}\boldsymbol{u} = \boldsymbol{b}$, $\boldsymbol{C} = [\boldsymbol{R} \quad -\boldsymbol{I}]$, $\boldsymbol{u} = \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{v} \end{bmatrix}$, $\boldsymbol{b} = \boldsymbol{0}$.

Alternating direction method of multipliers (ADMM)

When $\boldsymbol{u}$ has multiple component vectors, *e.g.*, $\boldsymbol{u} = \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{v} \end{bmatrix}$,
rewrite (modified) augmented Lagrangian in terms of all component vectors:

$$\begin{aligned} L(\boldsymbol{x}, \boldsymbol{v}; \boldsymbol{\eta}) &= \Psi(\boldsymbol{x}, \boldsymbol{v}) + \frac{\rho}{2} \|\boldsymbol{R}\boldsymbol{x} - \boldsymbol{v} - \boldsymbol{\eta}\|_2^2 \\ &= \frac{1}{2}\|\boldsymbol{y} - \boldsymbol{x}\|_2^2 + \beta \|\boldsymbol{v}\|_p + \frac{\rho}{2} \underbrace{\|\boldsymbol{R}\boldsymbol{x} - \boldsymbol{v} - \boldsymbol{\eta}\|_2^2}_{\textit{cf. } \text{penalty!}} \end{aligned}$$

because here $\boldsymbol{C}\boldsymbol{u} = \boldsymbol{R}\boldsymbol{x} - \boldsymbol{v}$.

Alternate between minimizing over each *component* vector:

$$\begin{aligned} \boldsymbol{x}^{(n+1)} &= \arg\min_{\boldsymbol{x}} L(\boldsymbol{x}, \boldsymbol{v}^{(n)}, \boldsymbol{\eta}^{(n)}) \\ \boldsymbol{v}^{(n+1)} &= \arg\min_{\boldsymbol{v}} L(\boldsymbol{x}^{(n+1)}, \boldsymbol{v}, \boldsymbol{\eta}^{(n)}) \\ \boldsymbol{\eta}^{(n+1)} &= \boldsymbol{\eta}^{(n)} + \left(\boldsymbol{R}\boldsymbol{x}^{(n+1)} - \boldsymbol{v}^{(n+1)}\right). \end{aligned}$$

Reasonably desirable convergence properties. (Inexact inner minimizations!)
Sufficient conditions on matrix $\boldsymbol{C}$.

(Eckstein & Bertsekas, Math. Prog., Apr. 1992)
(Douglas and Rachford, Tr. Am. Math. Soc., 1956, heat conduction problems)

ADMM for image denoising

Augmented Lagrangian:

$$L(\boldsymbol{x}, \boldsymbol{v}; \boldsymbol{\eta}) = \frac{1}{2}\|\boldsymbol{y} - \boldsymbol{x}\|_2^2 + \beta\,\|\boldsymbol{v}\|_p + \frac{\rho}{2}\|\boldsymbol{R}\boldsymbol{x} - \boldsymbol{v} - \boldsymbol{\eta}\|_2^2$$

Update of primal variable (unknown image):

$$\boldsymbol{x}^{(n+1)} = \arg\min_{\boldsymbol{x}} L(\boldsymbol{x}, \boldsymbol{v}^{(n)}, \boldsymbol{\eta}^{(n)}) = \underbrace{[\boldsymbol{I} + \rho\boldsymbol{R}'\boldsymbol{R}]^{-1}}_{\text{Wiener filter}} \left(\boldsymbol{y} + \rho\boldsymbol{R}'\left(\boldsymbol{v}^{(n)} + \boldsymbol{\eta}^{(n)}\right)\right)$$

Update of auxiliary variable: (No "corner rounding" needed for ℓ_1.)

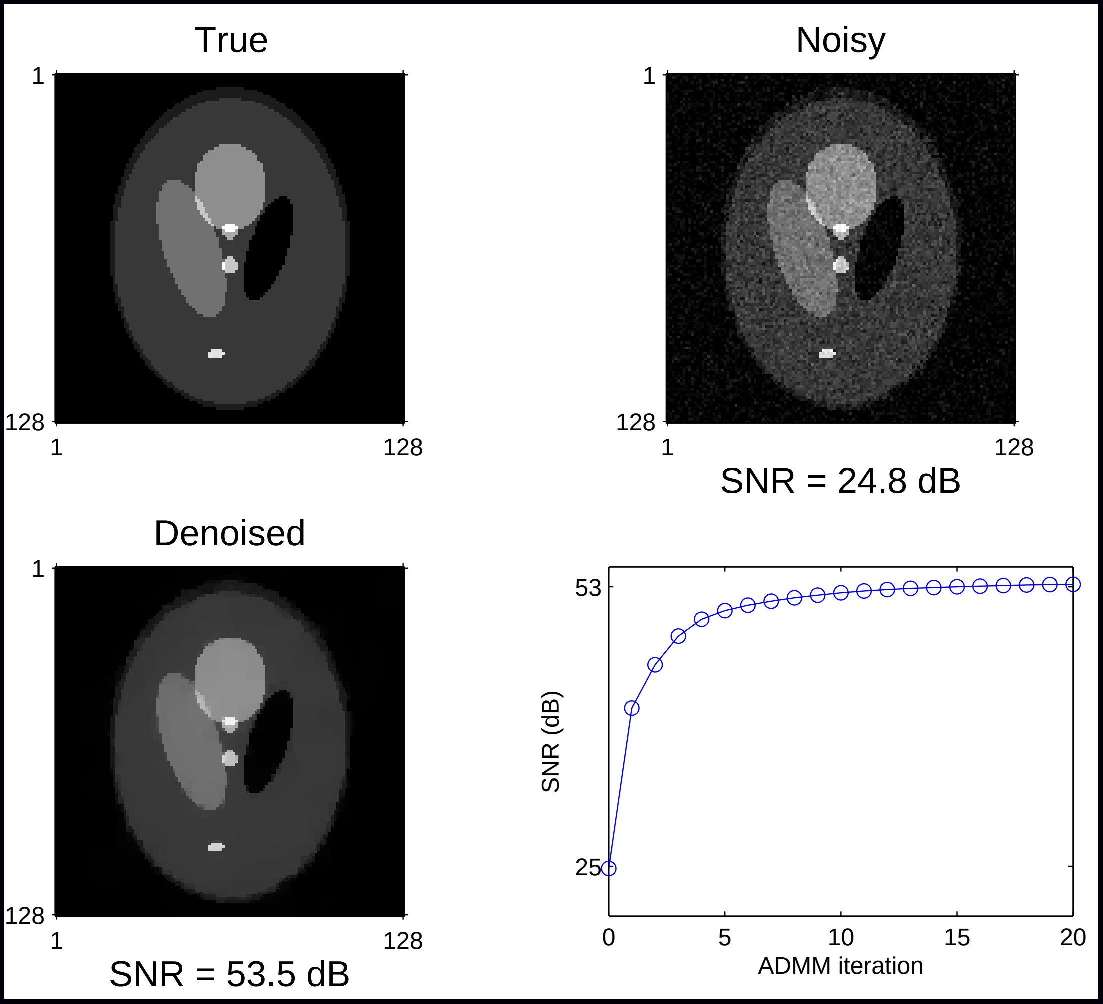
$$\boldsymbol{v}^{(n+1)} = \arg\min_{\boldsymbol{v}} L(\boldsymbol{x}^{(n+1)}, \boldsymbol{v}, \boldsymbol{\eta}^{(n)}) = \mathrm{shrink}\left(\boldsymbol{R}\boldsymbol{x}^{(n+1)} - \boldsymbol{\eta}^{(n)}; \beta/\rho, p\right)$$

Update of multiplier: $\boldsymbol{\eta}^{(n+1)} = \boldsymbol{\eta}^{(n)} + \left(\boldsymbol{R}\boldsymbol{x}^{(n+1)} - \boldsymbol{v}^{(n+1)}\right)$

Equivalent to "*split Bregman*" approach.
(Goldstein & Osher, SIAM J. Im. Sci. 2009)

Each update is simple and exact (non-iterative) if $[\boldsymbol{I} + \rho\boldsymbol{R}'\boldsymbol{R}]^{-1}$ is easy.

ADMM image denoising example



$\boldsymbol{R}$: horizontal and vertical finite differences (anisotropic TV),
$p = 1$ (*i.e.*, ℓ_1), $\beta = 1/2$, $\rho = 1$ (condition number of $(\boldsymbol{I} + \rho \boldsymbol{R}'\boldsymbol{R})$ is 9)

ADMM image denoising iterates

admm denoising movie

Image restoration

Image restoration models

Unrealistic model:

$$\underbrace{\boldsymbol{y}}_{\text{observed}} = \underbrace{\boldsymbol{A}}_{\text{blur}} \underbrace{\boldsymbol{x}}_{\text{unknown}} + \underbrace{\boldsymbol{\varepsilon}}_{\text{noise}}$$

Measured blurry image $\boldsymbol{y}$ and unknown image $\boldsymbol{x}$ have the same size.
$\boldsymbol{A}$ is a circulant matrix corresponding to a shift-invariant blur model.

Somewhat more realistic measurement model:

$$\boldsymbol{y} = \boldsymbol{T}\boldsymbol{A}\boldsymbol{x} + \boldsymbol{\varepsilon}$$

Measured blurry image $\boldsymbol{y}$ is smaller than unknown image $\boldsymbol{x}$.
$\boldsymbol{T}$ is a (fat) "truncation" matrix, akin to $[\mathbf{0}\ \boldsymbol{I}\ \mathbf{0}]$.
(S. Reeves, IEEE T-IP, Oct. 2005)

Image restoration with sparsity regularization

Regularized estimator:

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \underbrace{\frac{1}{2}\|\boldsymbol{y} - \boldsymbol{T}\boldsymbol{A}\boldsymbol{x}\|_2^2}_{\text{data fit}} + \beta \underbrace{\|\boldsymbol{R}\boldsymbol{x}\|_p}_{\text{sparsity}}.$$

Basic equivalent constrained optimization problem:

$$\min_{\boldsymbol{x},\boldsymbol{v}} \frac{1}{2}\|\boldsymbol{y} - \boldsymbol{T}\boldsymbol{A}\boldsymbol{x}\|_2^2 + \beta\|\boldsymbol{v}\|_p \text{ sub. to } \boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}.$$

Corresponding (modified) augmented Lagrangian (*cf.* "split Bregman"):

$$L(\boldsymbol{x},\boldsymbol{v};\boldsymbol{\eta}) = \frac{1}{2}\|\boldsymbol{y} - \boldsymbol{T}\boldsymbol{A}\boldsymbol{x}\|_2^2 + \beta\|\boldsymbol{v}\|_p + \frac{\rho}{2}\|\boldsymbol{R}\boldsymbol{x} - \boldsymbol{v} - \boldsymbol{\eta}\|_2^2$$

ADMM update of primal variable (unknown image):

$$\boldsymbol{x}^{(n+1)} = \arg\min_{\boldsymbol{x}} L(\boldsymbol{x},\boldsymbol{v}^{(n)},\boldsymbol{\eta}^{(n)}) = \left[\boldsymbol{A}'\boldsymbol{T}'\boldsymbol{T}\boldsymbol{A} + \rho\boldsymbol{R}'\boldsymbol{R}\right]^{-1}\left(\boldsymbol{A}'\boldsymbol{T}'\boldsymbol{y} + \rho\boldsymbol{R}'\left(\boldsymbol{v}^{(n)} + \boldsymbol{\eta}^{(n)}\right)\right)$$

Simple if $\boldsymbol{A}'\boldsymbol{A}$ and $\boldsymbol{R}'\boldsymbol{R}$ are circulant and $\boldsymbol{T} = \boldsymbol{I}$ (unrealistic).
Otherwise need iterative inner (quadratic) minimization: PCG.

Improved ADMM for image restoration

New equivalent constrained optimization problem:

$$\min_{\boldsymbol{x},\boldsymbol{u},\boldsymbol{v}} \frac{1}{2}\|\boldsymbol{y}-\boldsymbol{T}\,\boldsymbol{u}\|_2^2+\beta\,\|\boldsymbol{v}\|_p \text{ sub. to } \boldsymbol{v}=\boldsymbol{R}\boldsymbol{x}, \quad \boldsymbol{u}=\boldsymbol{A}\boldsymbol{x}.$$

(Antonios Matakos, Sathish Ramani, JF, IEEE T-IP, 2013, to appear)

Corresponding (modified) augmented Lagrangian:

$$L(\boldsymbol{x},\boldsymbol{u},\boldsymbol{v};\boldsymbol{\eta}_1,\boldsymbol{\eta}_2)=\frac{1}{2}\|\boldsymbol{y}-\boldsymbol{T}\,\boldsymbol{u}\|_2^2+\beta\,\|\boldsymbol{v}\|_p+\frac{\rho_1}{2}\|\boldsymbol{R}\boldsymbol{x}-\boldsymbol{v}-\boldsymbol{\eta}_1\|_2^2+\frac{\rho_2}{2}\|\boldsymbol{A}\boldsymbol{x}-\boldsymbol{u}-\boldsymbol{\eta}_2\|_2^2$$

ADMM update of primal variable (unknown image):

$$\arg\min_{\boldsymbol{x}} L(\boldsymbol{x},\boldsymbol{u},\boldsymbol{v},\boldsymbol{\eta}_1,\boldsymbol{\eta}_2)=\left[\rho_2\boldsymbol{A}'\boldsymbol{A}+\rho_1\boldsymbol{R}'\boldsymbol{R}\right]^{-1}\left(\rho_1\boldsymbol{R}'\left(\boldsymbol{v}+\boldsymbol{\eta}_1\right)+\rho_2\boldsymbol{A}'(\boldsymbol{u}+\boldsymbol{\eta}_2)\right)$$

Simple if $\boldsymbol{A}'\boldsymbol{A}$ and $\boldsymbol{R}'\boldsymbol{R}$ are circulant. No inner iterations needed!

ADMM update of new auxiliary variable $\boldsymbol{u}$:

$$\arg\min_{\boldsymbol{u}} L(\boldsymbol{x},\boldsymbol{u},\boldsymbol{v},\boldsymbol{\eta}_1,\boldsymbol{\eta}_2)=\underbrace{\left[\boldsymbol{T}'\boldsymbol{T}+\rho_2\boldsymbol{I}\right]^{-1}}_{\text{diagonal}}(\boldsymbol{T}'\boldsymbol{y}+\rho_2(\boldsymbol{A}\boldsymbol{x}-\boldsymbol{\eta}_2))$$

$\boldsymbol{v}$ update is shrinkage again. Very easy to code!

Image restoration results: quality

Measurement $\boldsymbol{y}$

Using circulant model with boundary preprocessing

ADMM with Reeves model

15×15 pixel uniform blur, 50dB BSNR $= 10\log\left(\mathrm{Var}\{\boldsymbol{TAx}\}/\sigma^2\right)$,
isotropic TV regularization, $\beta = 2^{-17}$

Qualitatively confirms Reeves model is preferable.

Image restoration results: iterations

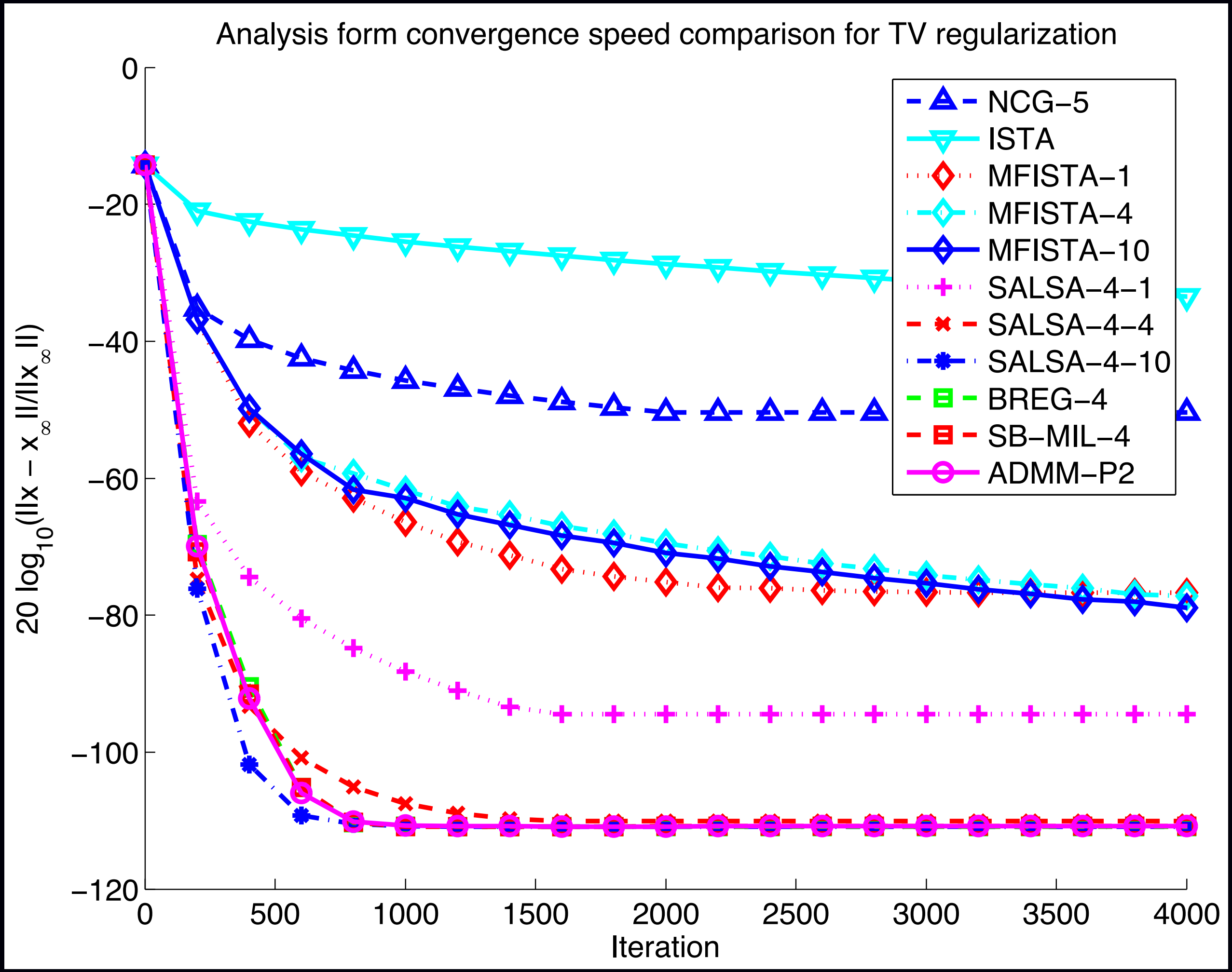
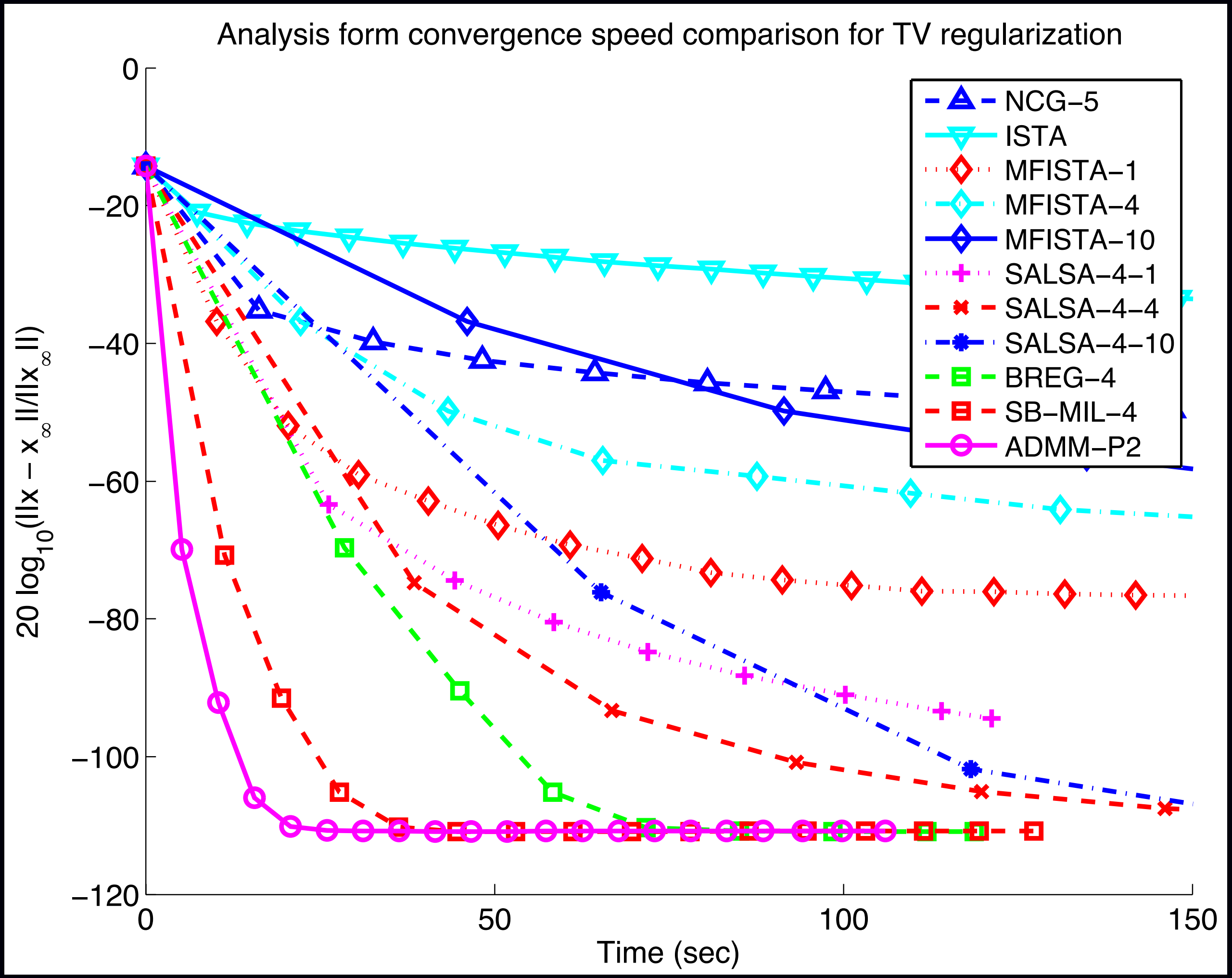


Image restoration results: speed



Proposed ADMM is fast due to non-iterative inner updates.

X-ray CT image reconstruction

Low-dose X-ray CT image reconstruction

Regularized estimator:

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}\succeq \boldsymbol{0}} \underbrace{\frac{1}{2}\|\boldsymbol{y}-\boldsymbol{A}\boldsymbol{x}\|_{\boldsymbol{W}}^2}_{\text{data fit}} + \beta \underbrace{\|\boldsymbol{R}\boldsymbol{x}\|_p}_{\text{sparsity}}.$$

Complications:

- $\boldsymbol{A}'\boldsymbol{A}$ is not circulant (but “approximately Toeplitz” in 2D)
- $\boldsymbol{A}'\boldsymbol{W}\boldsymbol{A}$ is highly shift variant due to huge dynamic range of weighting $\boldsymbol{W}$
- Non-quadratic (edge-preserving) regularization $\|\cdot\|_p$
- Nonnegativity constraint
- Large problem size

Basic ADMM for X-ray CT

Basic equivalent constrained optimization problem (*cf.* split Bregman):

$$\min_{\boldsymbol{x} \succeq \mathbf{0}, \boldsymbol{v}} \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{x}\|_{\boldsymbol{W}}^2 + \beta \|\boldsymbol{v}\|_p \text{ sub. to } \boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}.$$

Corresponding (modified) augmented Lagrangian (*cf.* “split Bregman”):

$$L(\boldsymbol{x}, \boldsymbol{v}; \boldsymbol{\eta}) = \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{x}\|_{\boldsymbol{W}}^2 + \beta \|\boldsymbol{v}\|_p + \frac{\rho}{2} \|\boldsymbol{R}\boldsymbol{x} - \boldsymbol{v} - \boldsymbol{\eta}\|_2^2$$

ADMM update of primal variable (unknown image):

$$\boldsymbol{x}^{(n+1)} = \arg\min_{\boldsymbol{x}} L(\boldsymbol{x}, \boldsymbol{v}^{(n)}, \boldsymbol{\eta}^{(n)}) = \left[\boldsymbol{A}'\boldsymbol{W}\boldsymbol{A} + \rho \boldsymbol{R}'\boldsymbol{R}\right]^{-1} \left(\boldsymbol{A}'\boldsymbol{W}'\boldsymbol{y} + \rho \boldsymbol{R}' \left(\boldsymbol{v}^{(n)} + \boldsymbol{\eta}^{(n)}\right)\right)$$

- Ignoring nonnegativity constraint
- $\left[\boldsymbol{A}'\boldsymbol{W}\boldsymbol{A} + \rho \boldsymbol{R}'\boldsymbol{R}\right]^{-1}$ requires iteration (*e.g.*, PCG) but hard to precondition
- Auxiliary variable $\boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}$ is enormous in 3D CT

Improved ADMM for X-ray CT

$$\min_{\boldsymbol{x} \succeq \mathbf{0}, \boldsymbol{u}, \boldsymbol{v}} \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{u}\|_{\boldsymbol{W}}^2 + \beta \|\boldsymbol{v}\|_p \text{ sub. to } \boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}, \quad \boldsymbol{u} = \boldsymbol{A}\boldsymbol{x}.$$

Corresponding (modified) augmented Lagrangian:

$$L(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{v}; \boldsymbol{\eta}_1, \boldsymbol{\eta}_2) = \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{u}\|_{\boldsymbol{W}}^2 + \beta \|\boldsymbol{v}\|_p + \frac{\rho_1}{2} \|\boldsymbol{R}\boldsymbol{x} - \boldsymbol{v} - \boldsymbol{\eta}_1\|_2^2 + \frac{\rho_2}{2} \|\boldsymbol{A}\boldsymbol{x} - \boldsymbol{u} - \boldsymbol{\eta}_2\|_2^2$$

ADMM update of primal variable (ignoring nonnegativity):

$$\arg\min_{\boldsymbol{x}} L(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{v}, \boldsymbol{\eta}_1, \boldsymbol{\eta}_2) = \left[\rho_2 \boldsymbol{A}'\boldsymbol{A} + \rho_1 \boldsymbol{R}'\boldsymbol{R}\right]^{-1} \left(\rho_1 \boldsymbol{R}' (\boldsymbol{v} + \boldsymbol{\eta}_1) + \rho_2 \boldsymbol{A}' (\boldsymbol{u} + \boldsymbol{\eta}_2)\right)$$

For 2D CT, $\left[\rho_2 \boldsymbol{A}'\boldsymbol{A} + \rho_1 \boldsymbol{R}'\boldsymbol{R}\right]^{-1}$ is approximately Toeplitz so a circulant preconditioner is very effective.

ADMM update of auxiliary variable $\boldsymbol{u}$:

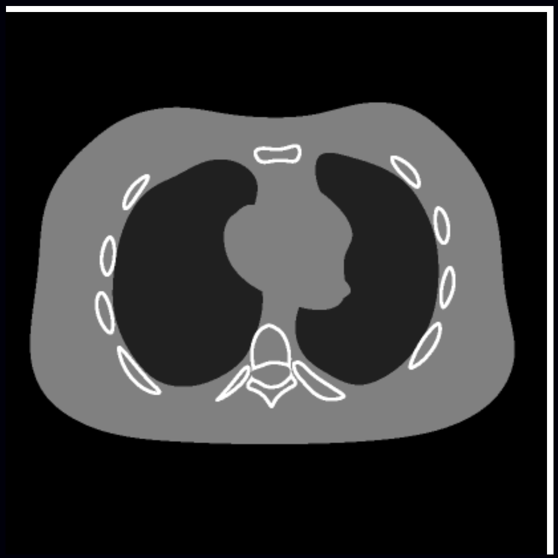
$$\arg\min_{\boldsymbol{u}} L(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{v}, \boldsymbol{\eta}_1, \boldsymbol{\eta}_2) = \underbrace{\left[\boldsymbol{W} + \rho_2 \boldsymbol{I}\right]^{-1}}_{\text{diagonal}} (\boldsymbol{W}\boldsymbol{y} + \rho_2 (\boldsymbol{A}\boldsymbol{x} - \boldsymbol{\eta}_2))$$

$\boldsymbol{v}$ update is shrinkage again. Reasonably simple to code.

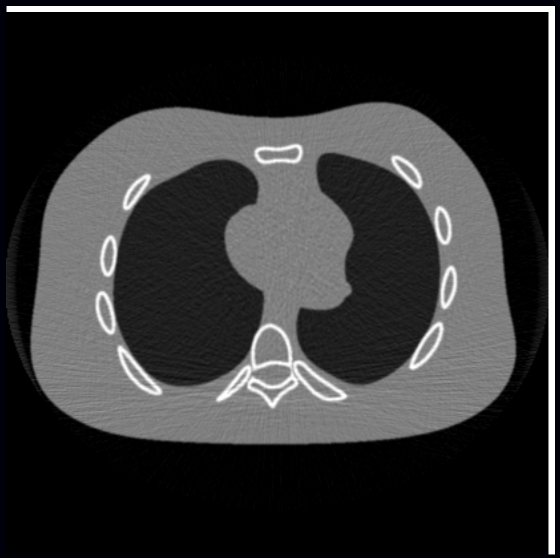
(Sathish Ramani & JF, IEEE T-MI, Mar. 2012)

2D X-ray CT image reconstruction results: quality

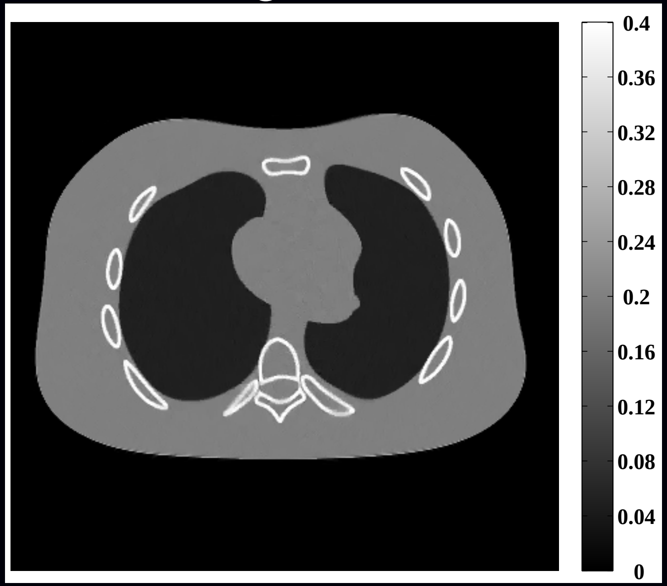
True



Hanning FBP

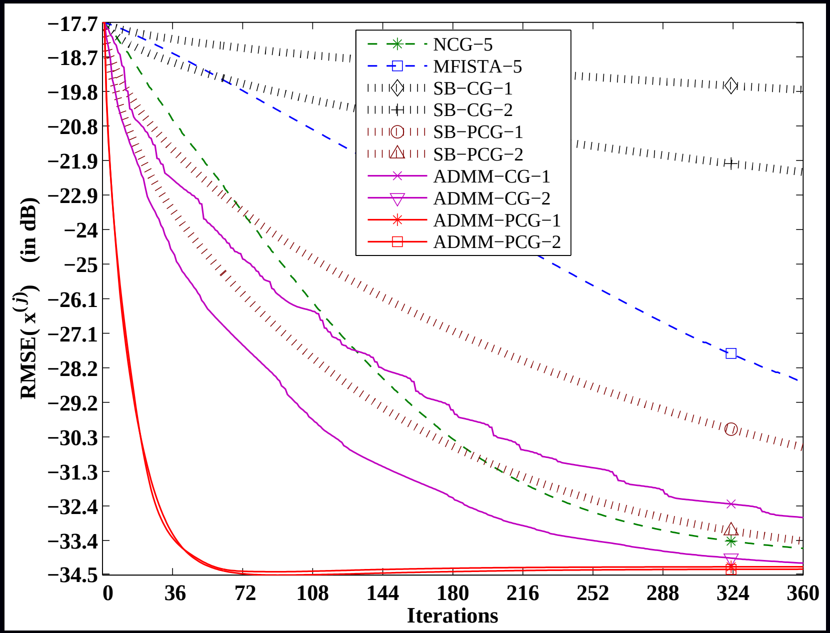


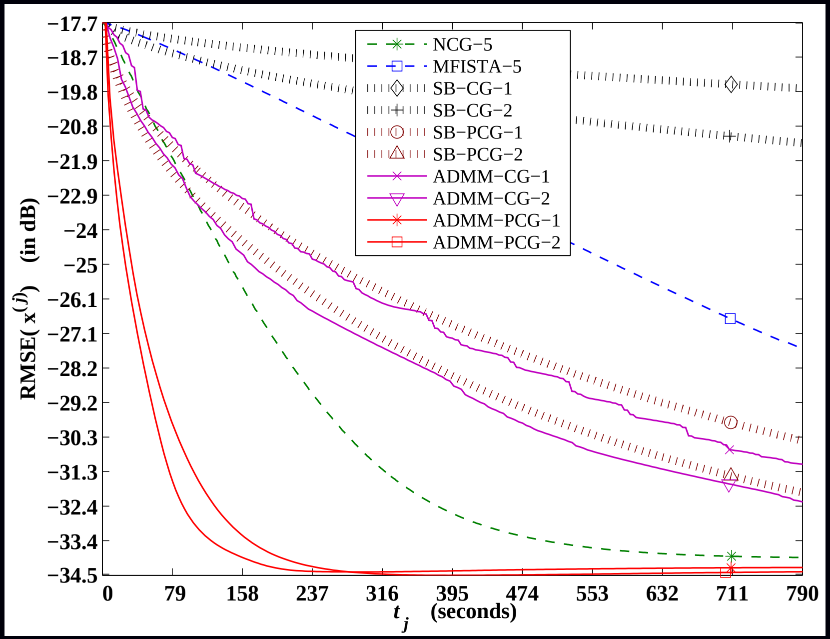
Regularized



PWLS with ℓ_1 regularization of shift-invariant Haar wavelet transform.
No nonnegativity constraint, but probably unimportant if well-regularized.

2D X-ray CT image reconstruction results: speed





Circulant preconditioner for $\left[\rho_2 \boldsymbol{A}'\boldsymbol{A} + \rho_1 \boldsymbol{R}'\boldsymbol{R}\right]^{-1}$ is crucial to acceleration.

Similar results for real head CT scan in paper.

Lower-memory ADMM for X-ray CT

$$\min_{x,u,z \succeq 0} \frac{1}{2} \|y - u\|_W^2 + \beta \|Rz\|_p \text{ sub. to } z = x, \quad u = Ax.$$

(M McGaffin, S Ramani, JF, SPIE 2012)

Corresponding (modified) augmented Lagrangian:

$$L(x, u, z; \eta_1, \eta_2) = \frac{1}{2} \|y - u\|_W^2 + \beta \|Rz\|_p + \frac{\rho_1}{2} \|x - z - \eta_1\|_2^2 + \frac{\rho_2}{2} \|Ax - u - \eta_2\|_2^2$$

ADMM update of primal variable (nonnegativity not required, use PCG):

$$\arg\min_x L(x, u, z, \eta_1, \eta_2) = \left[\rho_2 A'A + \rho_1 I\right]^{-1} \left(\rho_1 (z + \eta_1) + \rho_2 A' (u + \eta_2)\right).$$

ADMM update of auxiliary variable z:

$$\arg\min_{z \succeq 0} L(x, u, z, \eta_1, \eta_2) = \arg\min_{z \succeq 0} \frac{\rho_1}{2} \|x - z - \eta_1\|_2^2 + \beta \|Rz\|_p.$$

Use nonnegatively constrained, edge-preserving image denoising.

ADMM updates of auxiliary variables u and v same as before.
Variations...

3D X-ray CT image reconstruction results

Awaiting better preconditioner for $\left[\rho_2 \boldsymbol{A}'\boldsymbol{A} + \rho_1 \boldsymbol{I}\right]^{-1}$

Image reconstruction for parallel MRI

Model-based image reconstruction in parallel MR

Undersampled Cartesian k-space, multiple receive coils, ...

Regularized estimator:

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \underbrace{\frac{1}{2} \|\boldsymbol{y} - \boldsymbol{F}\boldsymbol{S}\boldsymbol{x}\|_2^2}_{\text{data fit}} + \beta \underbrace{\|\boldsymbol{R}\boldsymbol{x}\|_p}_{\text{sparsity}}.$$

$\boldsymbol{F}$ is under-sampled DFT matrix (fat)

Features:
- coil sensitivity matrix $\boldsymbol{S}$ is block diagonal (Pruessmann *et al.*, MRM, Nov. 1999)
- $\boldsymbol{F}'\boldsymbol{F}$ is circulant

Complications:
- Data-fit Hessian $\boldsymbol{S}'\boldsymbol{F}'\boldsymbol{F}\boldsymbol{S}$ is highly shift variant due to coil sensitivity maps
- Non-quadratic (edge-preserving) regularization $\|\cdot\|_p$
- Complex quantities
- Large problem size (if 3D)

Basic ADMM for parallel MRI

Basic equivalent constrained optimization problem (*cf.* split Bregman):

$$\min_{\boldsymbol{x},\boldsymbol{v}} \frac{1}{2}\|\boldsymbol{y} - \boldsymbol{F}\boldsymbol{S}\boldsymbol{x}\|_2^2 + \beta\|\boldsymbol{v}\|_p \text{ sub. to } \boldsymbol{v} = \boldsymbol{R}\boldsymbol{x}.$$

Corresponding (modified) augmented Lagrangian (*cf.* "split Bregman"):

$$L(\boldsymbol{x},\boldsymbol{v};\boldsymbol{\eta}) = \frac{1}{2}\|\boldsymbol{y} - \boldsymbol{F}\boldsymbol{S}\boldsymbol{x}\|_2^2 + \beta\|\boldsymbol{v}\|_p + \frac{\rho}{2}\|\boldsymbol{R}\boldsymbol{x} - \boldsymbol{v} - \boldsymbol{\eta}\|_2^2$$

(Skipping technical details about complex vectors.)

ADMM update of primal variable (unknown image):

$$\boldsymbol{x}^{(n+1)} = \arg\min_{\boldsymbol{x}} L(\boldsymbol{x},\boldsymbol{v}^{(n)},\boldsymbol{\eta}^{(n)}) = \left[\boldsymbol{S}'\boldsymbol{F}'\boldsymbol{F}\boldsymbol{S} + \rho\boldsymbol{R}'\boldsymbol{R}\right]^{-1}\left(\boldsymbol{S}'\boldsymbol{F}'\boldsymbol{y} + \rho\boldsymbol{R}'\left(\boldsymbol{v}^{(n)} + \boldsymbol{\eta}^{(n)}\right)\right)$$

- $\left[\boldsymbol{S}'\boldsymbol{F}'\boldsymbol{F}\boldsymbol{S} + \rho\boldsymbol{R}'\boldsymbol{R}\right]^{-1}$ requires iteration (*e.g.*, PCG) but hard to precondition
- (Trivial for single coil case with $\boldsymbol{S} = \boldsymbol{I}$.)
- The "problem" matrix is on opposite side:
  - MRI: $\boldsymbol{F}\boldsymbol{S}$
  - Restoration: $\boldsymbol{T}\boldsymbol{A}$

Improved ADMM for parallel MRI

$$\min_{x,u,v,z} \frac{1}{2}\|y - F\,u\|_2^2 + \beta\,\|v\|_p \text{ sub. to } v = Rz, \quad u = Sx, \quad z = x.$$

Corresponding (modified) augmented Lagrangian:

$$\frac{1}{2}\|y - F\,u\|_2^2 + \beta\,\|v\|_p + \frac{\rho_1}{2}\|Rz - v - \eta_1\|_2^2 + \frac{\rho_2}{2}\|Sx - u - \eta_2\|_2^2 + \frac{\rho_3}{2}\|x - z - \eta_3\|_2^2$$

ADMM update of primal variable

$$\arg\min_x L(x, u, v, z; \eta_1, \eta_2, \eta_3) = \underbrace{\left[\rho_2 S' S + \rho_3 I\right]^{-1}}_{\text{diagonal}} \left(\rho_2 S' \,(u + \eta_2) + \rho_3 (z + \eta_3)\right)$$

ADMM update of auxiliary variables:

$$\arg\min_u L(x, u, v, z; \eta_1, \eta_2, \eta_3) = \underbrace{\left[F' F + \rho_2 I\right]^{-1}}_{\text{circulant}} (F' y + \rho_2 (Sx - \eta_2))$$

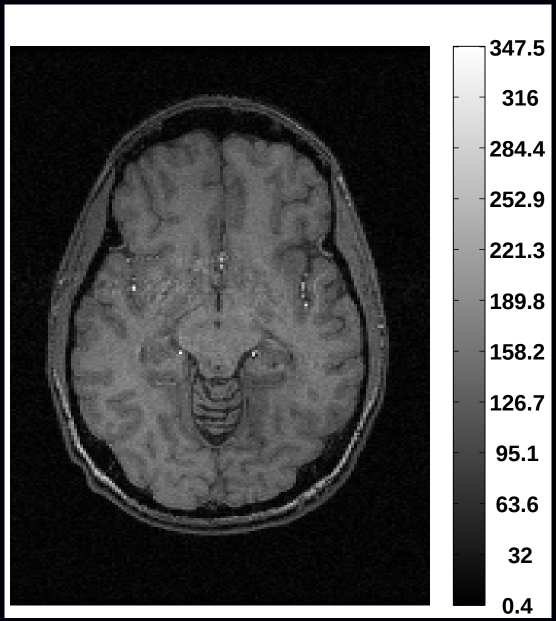
$$\arg\min_z L(x, u, v, z; \eta_1, \eta_2, \eta_3) = \underbrace{\left[\rho_1 R' R + \rho_3 I\right]^{-1}}_{\text{circulant}} (\rho_1 R' (v + \eta_1) + \rho_3 (x - \eta_3))$$

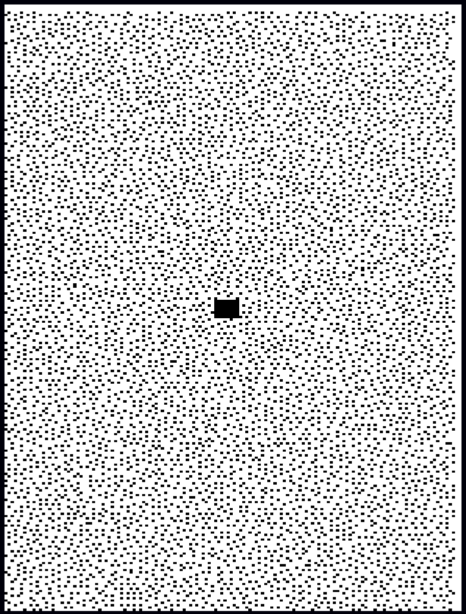
v update is shrinkage again.

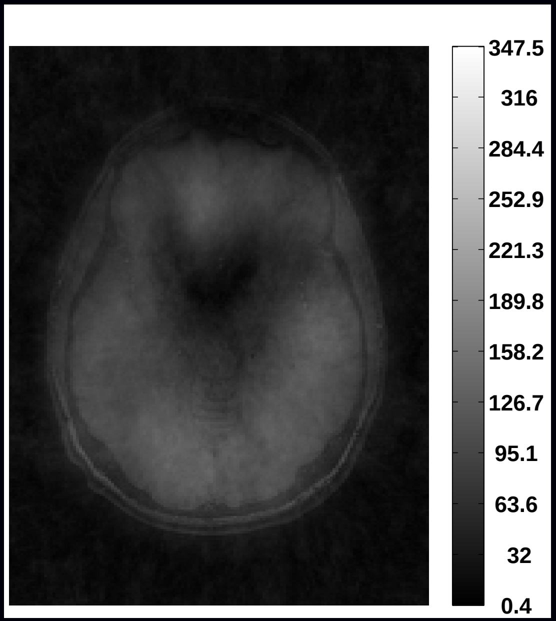
Simple, but does not satisfy sufficient conditions.

(Sathish Ramani & JF, IEEE T-MI, Mar. 2011)

2.5D parallel MR image reconstruction results: data

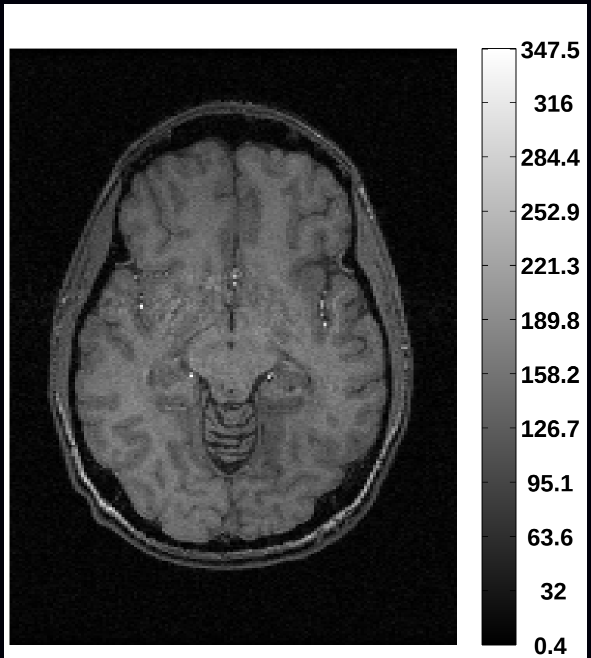


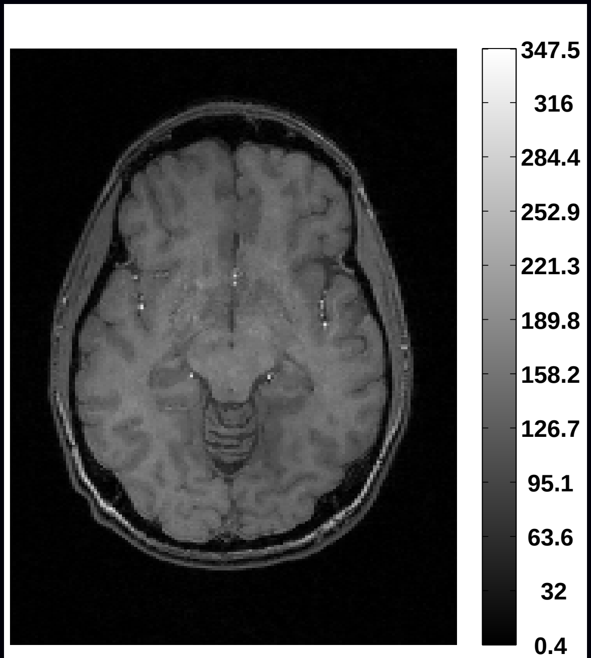


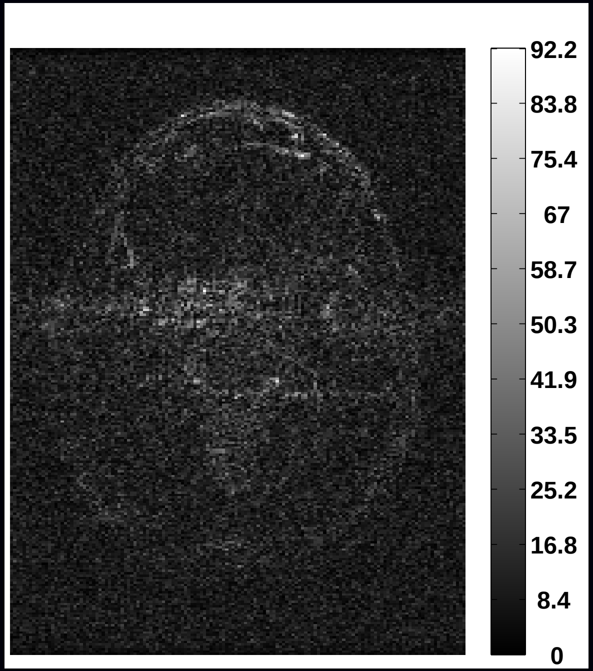


Fully sampled body coil image of human brain
Poisson-disk-based k-space sampling, 16% sampling (acceleration 6.25)
Square-root of sum-of-squares inverse FFT of zero-filled k-space data

2.5D parallel MR image reconstruction results: IQ

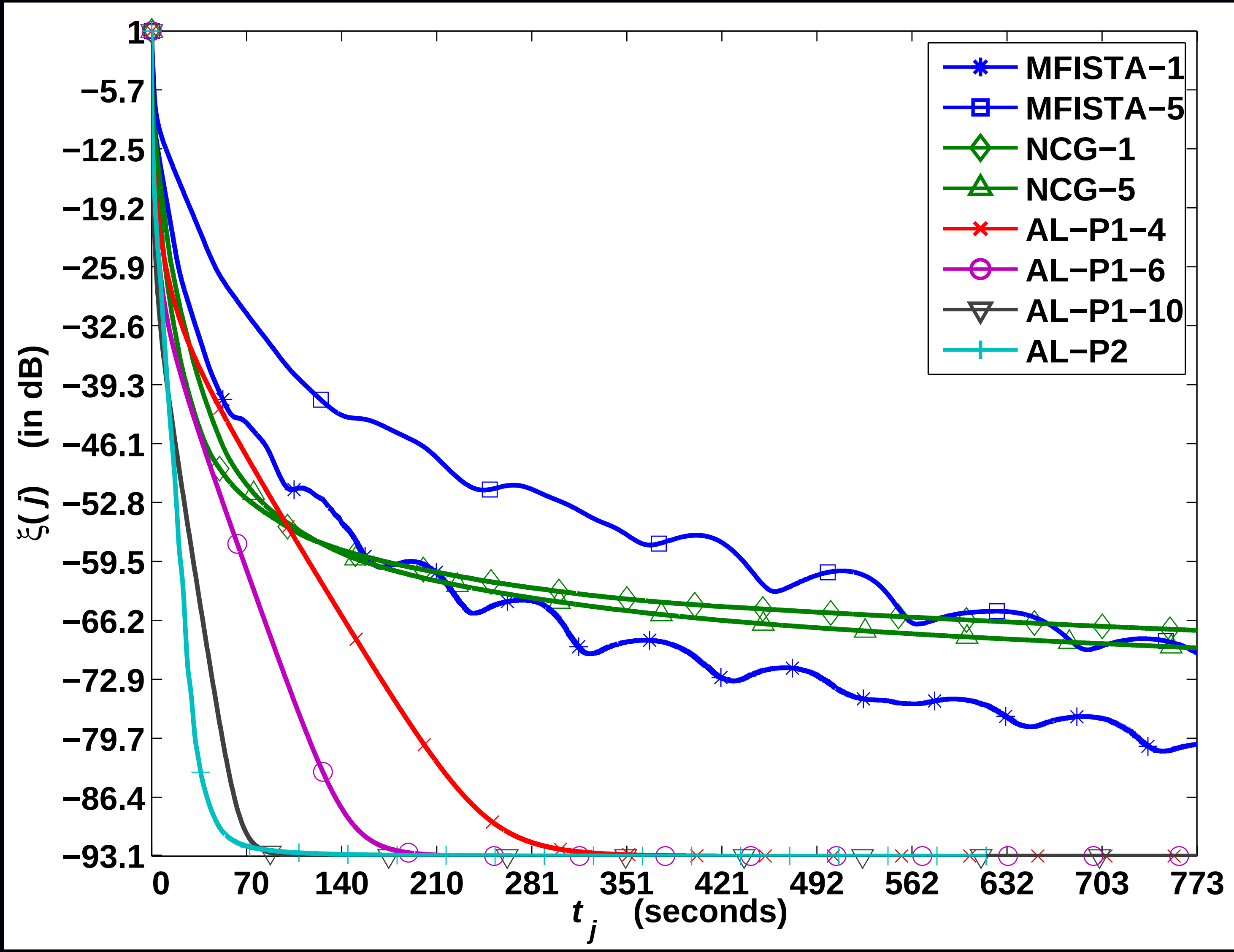






- Fully sampled body coil image of human brain
- Regularized reconstruction $\boldsymbol{x}^{(\infty)}$ (1000s of iterations of MFISTA)
  (A Beck & M Teboulle, SIAM J. Im. Sci, 2009)
  Combined TV and ℓ_1 norm of two-level undecimated Haar wavelets
- Difference image magnitude

2.5D parallel MR image reconstruction results: speed



AL approach converges to $\boldsymbol{x}^{(\infty)}$ much faster than MFISTA and CG

Current and future directions with ADMM

- Motion-compensated image reconstruction: $\boldsymbol{y} = \boldsymbol{A}\boldsymbol{T}(\boldsymbol{\alpha})\boldsymbol{x} + \boldsymbol{\varepsilon}$
  (J H Cho, S Ramani, JF, 2nd CT meeting, 2012)
  (J H Cho, S Ramani, JF, IEEE Stat. Sig. Proc. W., 2012)
- Dynamic image reconstruction
- Improved preconditioners for ADMM for 3D CT
  (M McGaffin and JF, Submitted to Fully 3D 2013)
- Combining ADMM with ordered subsets (OS) methods
  (H Nien and JF, Submitted to Fully 3D 2013)
- Generalize parallel MRI algorithm to include spatial support constraint
  (M Le, S Ramani, JF, To appear at ISMRM 2013)
- Non-Cartesian MRI (combine optimization transfer and variable splitting)
  (S Ramani and JF, ISBI 2013, to appear.)
- SPECT-CT reconstruction with non-local means regularizer
  (S Y Chun, Y K Dewaraja, JF, Submitted to Fully 3D 2013)
- Estimation of coil sensitivity maps (quadratic problem!)
  (M J Allison, S Ramani, JF, IEEE T-MI, 2013, to appear)
- L1-SPIRiT for non-Cartesian parallel MRI (D S Weller, S Ramani, JF, IEEE T-MI, 2013, submitted)
- Multi-frame super-resolution
- Selection of AL penalty parameter ρ to optimize convergence rate

- Other non-ADMM methods...

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- Tom Chenevert
- Charles Meyer

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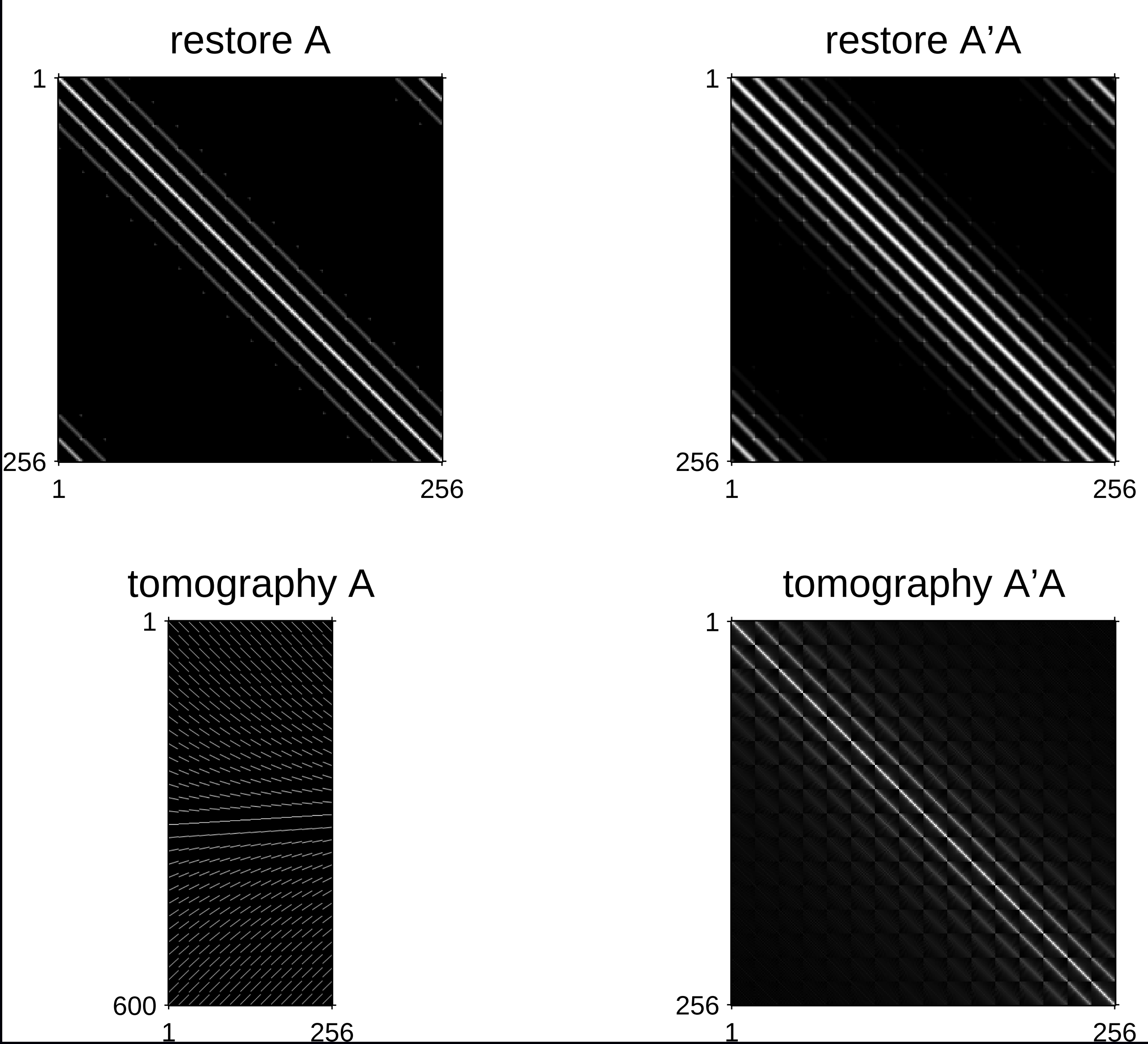
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