

Phase

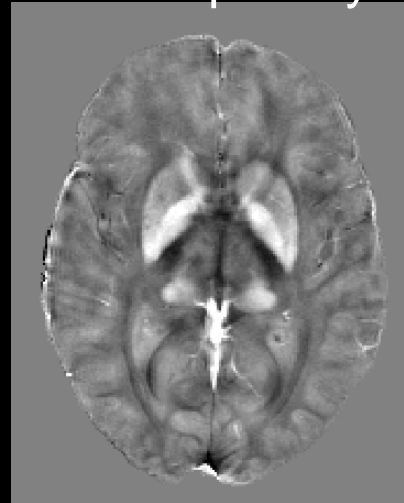


0.6 seconds



inversion

Susceptibility



Regularized QSM in Seconds

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Salt Lake City, Utah, USA

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"Discovery, Innovation & Application - Advancing MR for Improved Health"

Declaration of Relevant Financial Interests or Relationships

Speaker Name: Berkin Bilgic

I have no relevant financial interest or relationship to disclose with regard to the subject matter of this presentation.

Quantitative Susceptibility Mapping (QSM)

- Quantitative Susceptibility Mapping (QSM) aims to quantify tissue magnetic susceptibility χ
- Susceptibility correlates well with tissue iron concentration, especially in iron rich deep gray matter structures [1,2]

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$$\mathbf{F}^H \mathbf{D} \mathbf{F} \chi = \phi$$

diagonal matrix DFT unknown susceptibility unwrapped phase

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↓ ↓

to be estimated measured

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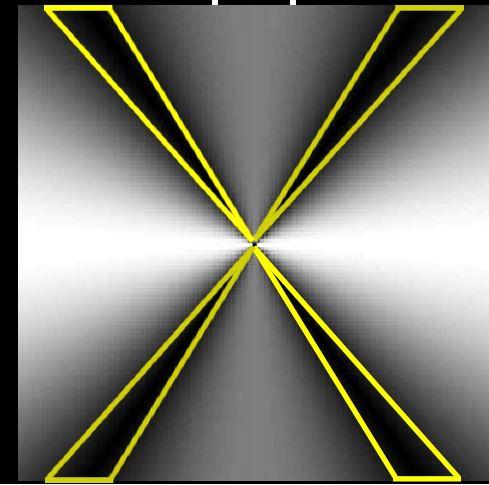
$$\mathbf{F}^H \mathbf{D} \mathbf{F} \chi = \phi$$

$$\mathbf{D} = \frac{1}{3} - \frac{k_z^2}{k^2}$$



Undersamples k-space
on a conical surface

$|\mathbf{D}|$



Regularized QSM

- Solution of inverse problem is facilitated by regularization that imposes prior knowledge [1]

$$\chi = \underset{\chi}{\operatorname{argmin}} \underbrace{\|\phi - \mathbf{F}^H \mathbf{D} \mathbf{F} \chi\|_2^2}_{\text{data consistency}} + \lambda \cdot \underbrace{\|\mathbf{G} \chi\|_2^2}_{\ell_2 \text{ over gradients}}$$

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$$\mathbf{G} = \begin{bmatrix} \mathbf{G}_x \\ \mathbf{G}_y \\ \mathbf{G}_z \end{bmatrix}$$

gradient in 3D

Regularized QSM

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- Prior: underlying susceptibility map is smooth

Regularized QSM

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- Existing methods work iteratively [1,2], requiring
~30 minutes for a 3D volume → not feasible
- We address this with fast recon in ~1 second

Regularized QSM

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- Solution can be evaluated in closed-form

$$\chi = (\mathbf{F}^H \mathbf{D}^2 \mathbf{F} + \lambda \cdot \mathbf{G}^H \mathbf{G})^{-1} \mathbf{F}^H \mathbf{D} \mathbf{F} \phi$$

- The minimizer can be computed efficiently given that the matrix inversion is rapidly performed

Fast Regularized QSM

- Solution can be evaluated in closed-form

$$\chi = (\mathbf{F}^H \mathbf{D}^2 \mathbf{F} + \lambda \cdot \mathbf{G}^H \mathbf{G})^{-1} \mathbf{F}^H \mathbf{D} \mathbf{F} \phi$$

Fast Regularized QSM

- Solution can be evaluated in closed-form

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- Gradient along x-axis can be represented in k-space by multiplication with a diagonal matrix \mathbf{E}_x

$$\mathbf{G}_x = \mathbf{F}^H \mathbf{E}_x \mathbf{F} \quad \text{where } \mathbf{E}_x(i, i) = 1 - e^{(-2\pi\sqrt{-1}k_x(i,i)/N_x)}$$

Fast Regularized QSM

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- \mathbf{E}_x is simply the k-space representation of the difference operator $\delta_x - \delta_{x-1}$

Fast Regularized QSM

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- With this formulation, closed-form solution becomes

$$\chi = \mathbf{F}^H \mathbf{D} \underbrace{[\mathbf{D}^2 + \lambda \cdot (\mathbf{E}_x^2 + \mathbf{E}_y^2 + \mathbf{E}_z^2)]}_{\text{all matrices diagonal}}^{-1} \mathbf{F} \phi$$

all matrices diagonal

Fast Regularized QSM

- Solution can be evaluated in closed-form

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- **Total cost:** Two FFTs and multiplication of diagonal matrices

Contributions

- Proposed closed-form method is **1000-times faster** than iterative Conjugate Gradient solver in [1,2]

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- Automatic selection of regularization parameter λ is possible:
Trace L-curve with closed-form method in a minute

Contributions

- Proposed closed-form method is **1000-times faster** than iterative Conjugate Gradient solver in [1,2]
- Proposed method yields exact minimizer while iterative methods converge to it
- Automatic selection of regularization parameter λ is possible:
Trace L-curve with closed-form method in a minute
- Combined with fast background removal methods like SHARP [3], enables real-time QSM

Comparison of methods

- Proposed method:

- ❖ Closed form QSM

- Previous method:

- ❖ Iterative QSM with Conjugate Gradient [1,2]
converges to closed-form solution

[1] de Rochefort *et al.*, MRM 2010

[2] Bilgic *et al.*, Neuroimage 2012

[3] Shmueli *et al.*, MRM 2009

Comparison of methods

- Proposed method:

- ❖ Closed form QSM

- Previous method:

- ❖ Iterative QSM with Conjugate Gradient [1,2]
converges to closed-form solution

- ❖ Initialize with Thresholded K-space Division map [3]

- ❖ Terminate when change in susceptibility is less than 1%

[1] de Rochefort *et al.*, MRM 2010

[2] Bilgic *et al.*, Neuroimage 2012

[3] Shmueli *et al.*, MRM 2009

Regularized QSM Methods

- Numerical Phantom

- Three compartments (gray, white, CSF) with constant χ
- Phase ϕ computed from true χ , and Gaussian noise added
- Regularization param λ chosen to minimize RMSE in χ recon

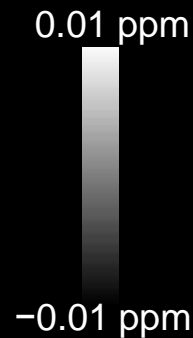
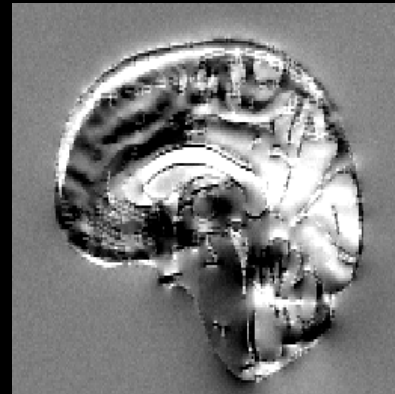
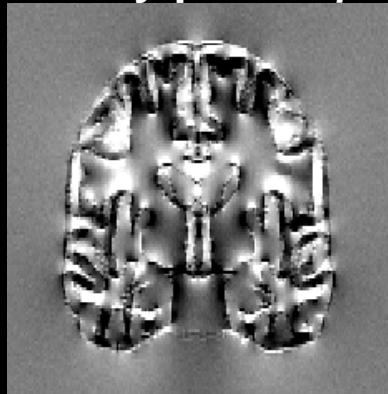
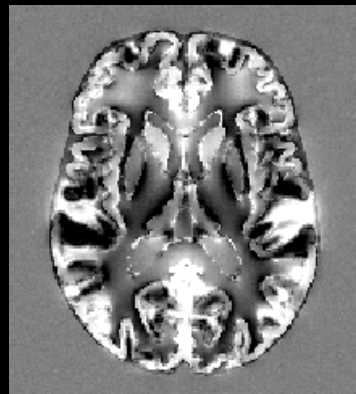
Regularized QSM Methods

- Numerical Phantom
 - Three compartments (gray, white, CSF) with constant χ
 - Phase ϕ computed from true χ , and Gaussian noise added
 - Regularization param λ chosen to minimize RMSE in χ recon
- In Vivo 3D SPGR
 - Healthy subject at 1.5T with resolution $0.94 \times 0.94 \times 2.5 \text{mm}^3$
 - Regularization parameter λ chosen based on L-curve
 - Background phase removal with dipole fitting [1]
- Computations done on workstation with 32 CPU processors and 128 GB memory

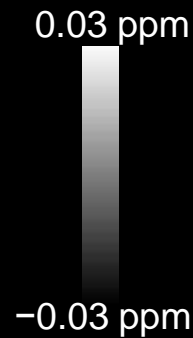
Numerical Phantom

Noisy phase ϕ

error due to noise:
5.0% RMSE

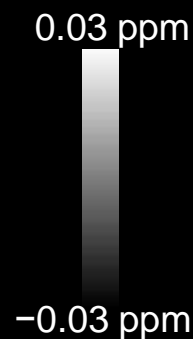
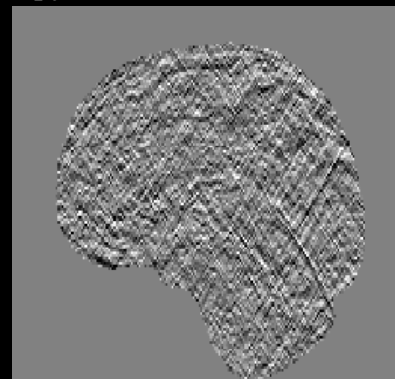
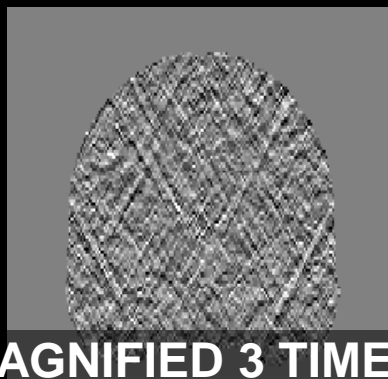
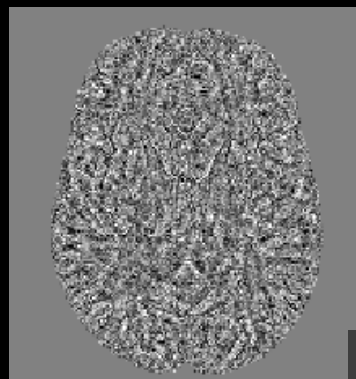


Closed-form QSM in 1.1 seconds



True χ
known

Closed-form QSM error relative to True χ

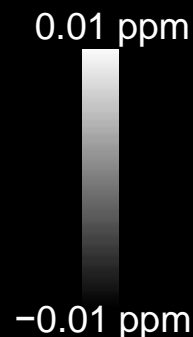
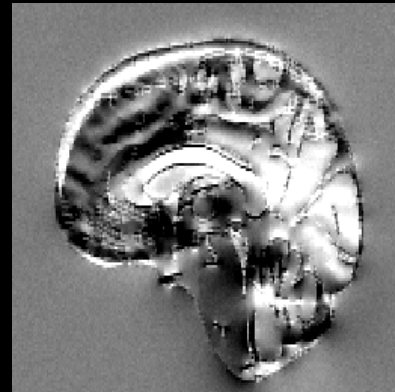
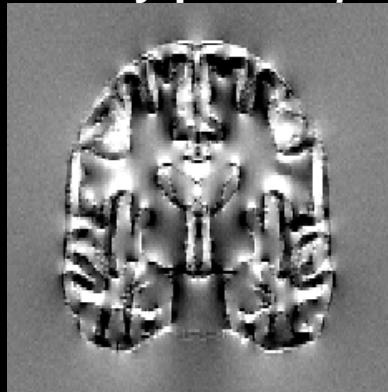
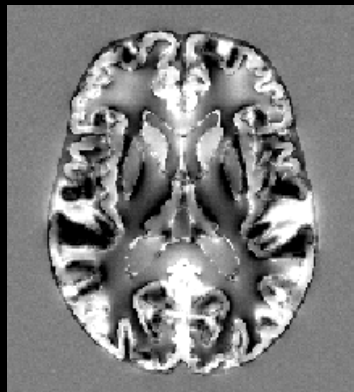


MAGNIFIED 3 TIMES

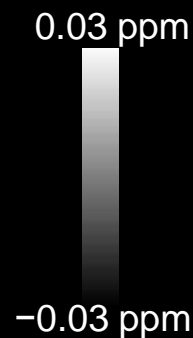
Numerical Phantom

Noisy phase ϕ

error due to noise:
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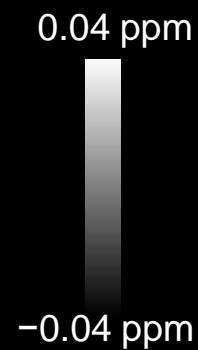
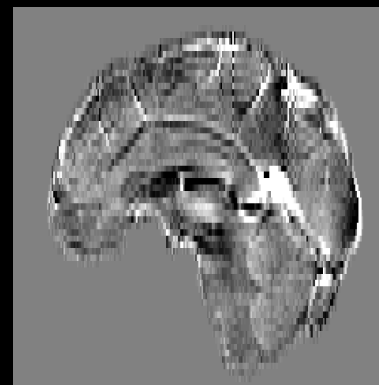
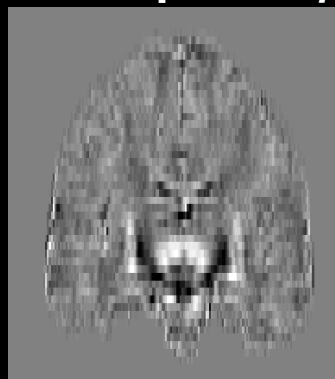
Closed-form QSM in 1.1 seconds



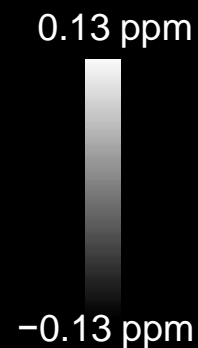
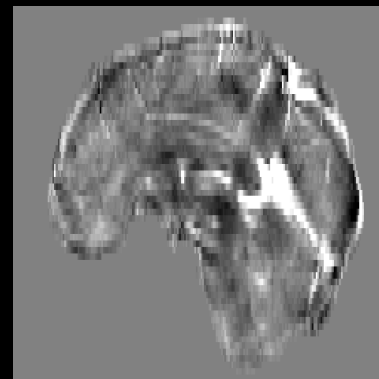
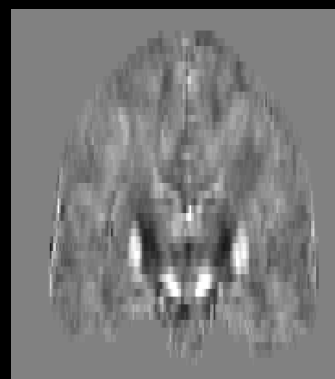
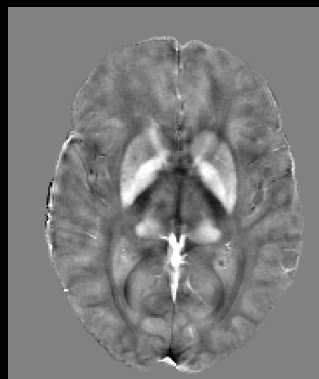
QSM Method	Recon Time	Error relative to True χ
Proposed Closed-Form	1.1 seconds	16.1 % RMSE
Conjugate Grad, 80 iters	33 minutes	16.8 % RMSE

In Vivo QSM

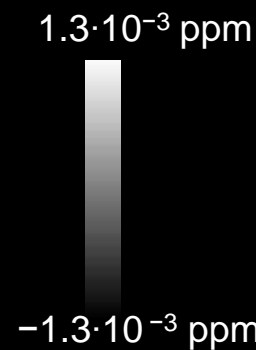
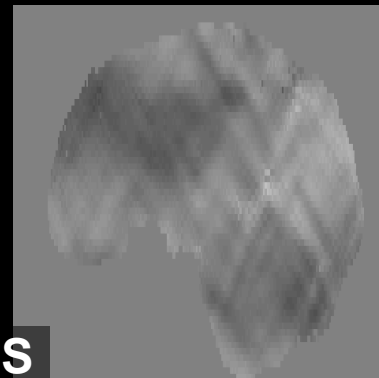
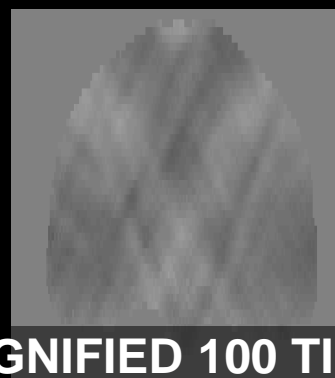
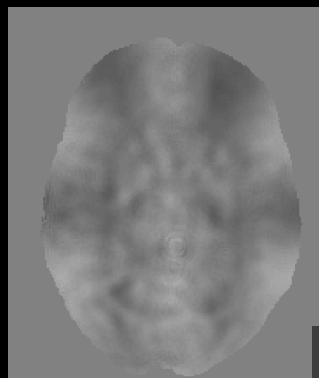
Tissue phase ϕ



Closed-form QSM in 0.6 seconds



Closed-form and Iterative QSM difference: 0.6%

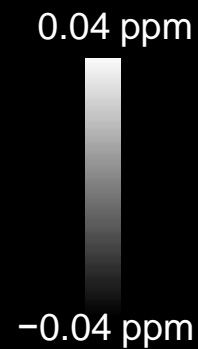
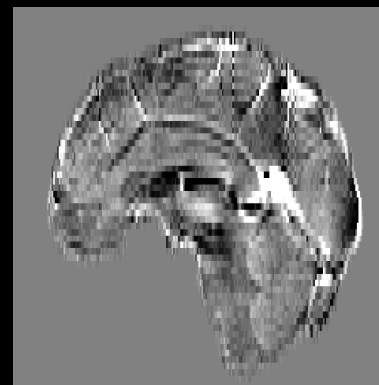
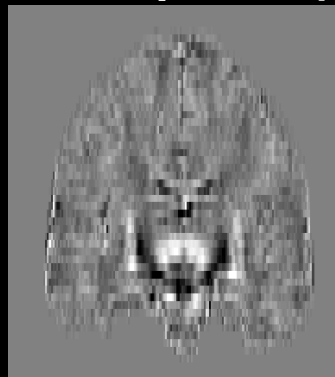


True χ
not known

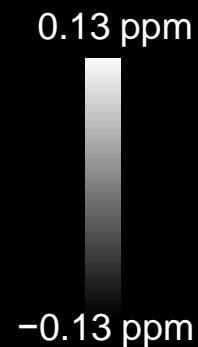
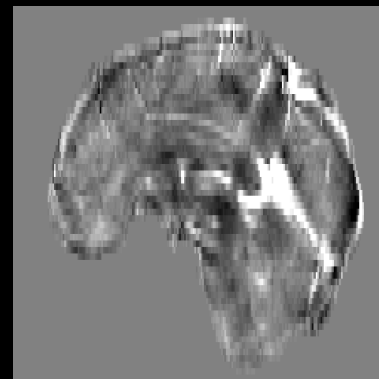
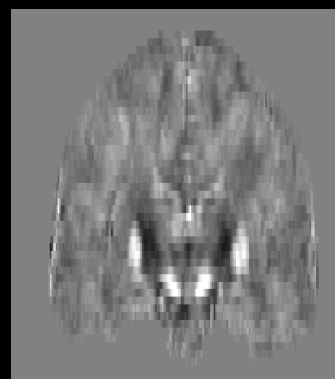
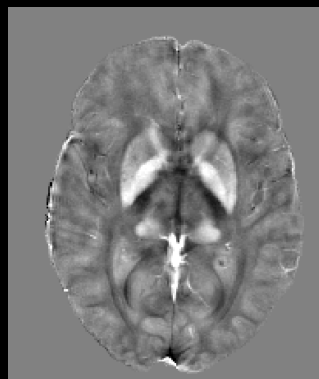
MAGNIFIED 100 TIMES

In Vivo QSM

Tissue phase ϕ



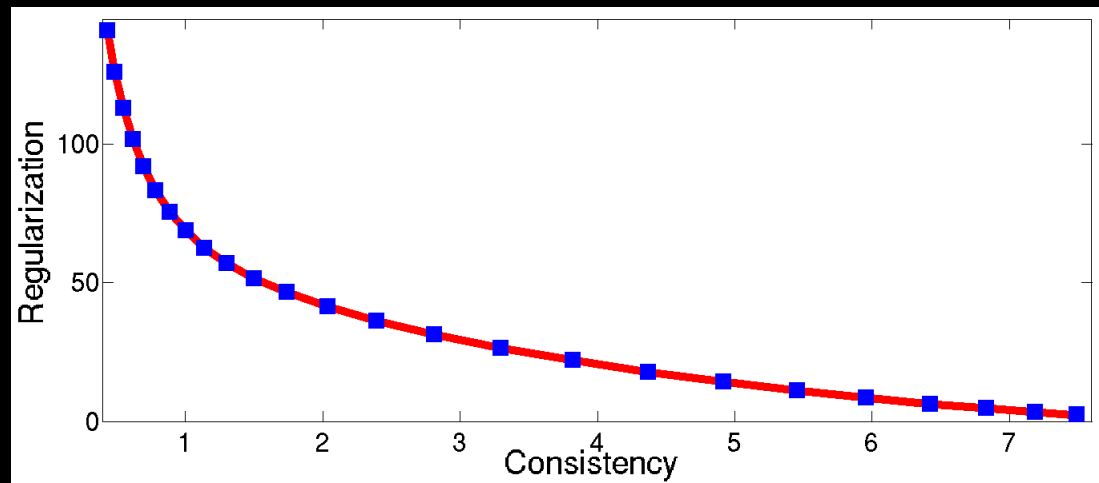
Closed-form QSM in 0.6 seconds



QSM Method	Recon Time
Proposed Closed-Form	0.6 seconds
Conjugate Gradient, 80 iters	18 minutes

Tracing the L-curve

$$\|G\chi\|_2$$

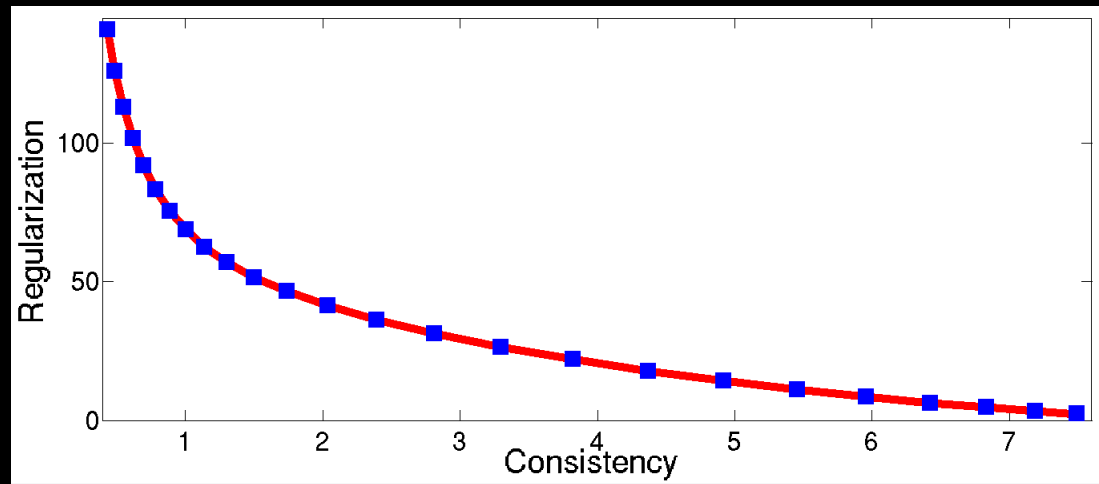


$$\|\phi - F^H DF\chi\|_2$$

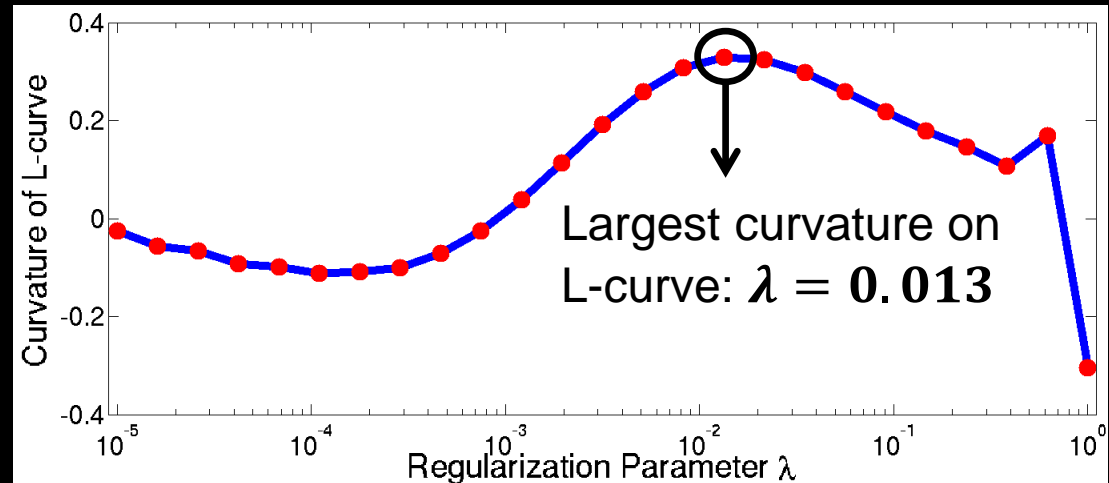
- Computing χ for 25 different values of λ : 50 seconds

Tracing the L-curve

$$\|G\chi\|_2$$



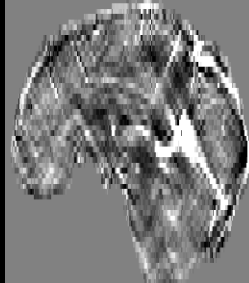
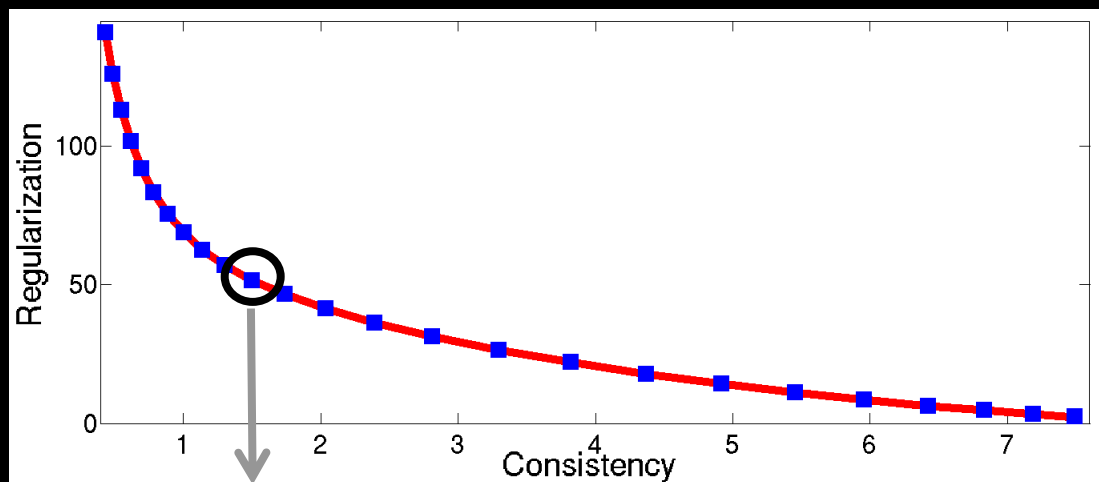
$$\|\phi - F^H DF\chi\|_2$$



- Computing χ for 25 different values of λ : 50 seconds
- Find optimal λ by computing the curvature of L-curve

Tracing the L-curve

$$\|G\chi\|_2$$

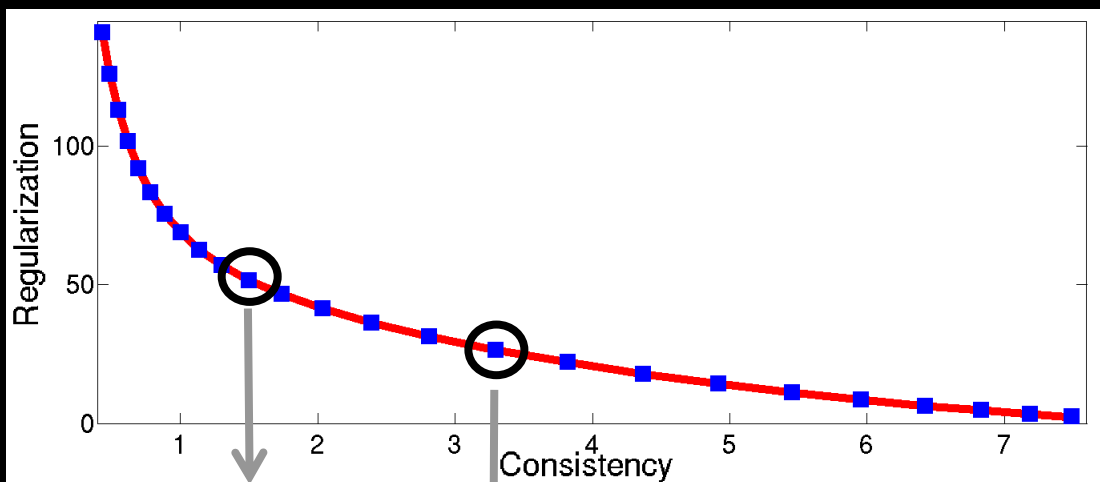


Under-regularized
 $\lambda = 0.001$

$$\|\phi - F^H DF\chi\|_2$$

Tracing the L-curve

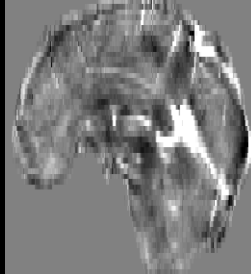
$$\|G\chi\|_2$$



$$\|\phi - F^H D F \chi\|_2$$



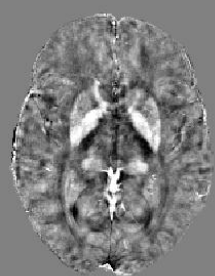
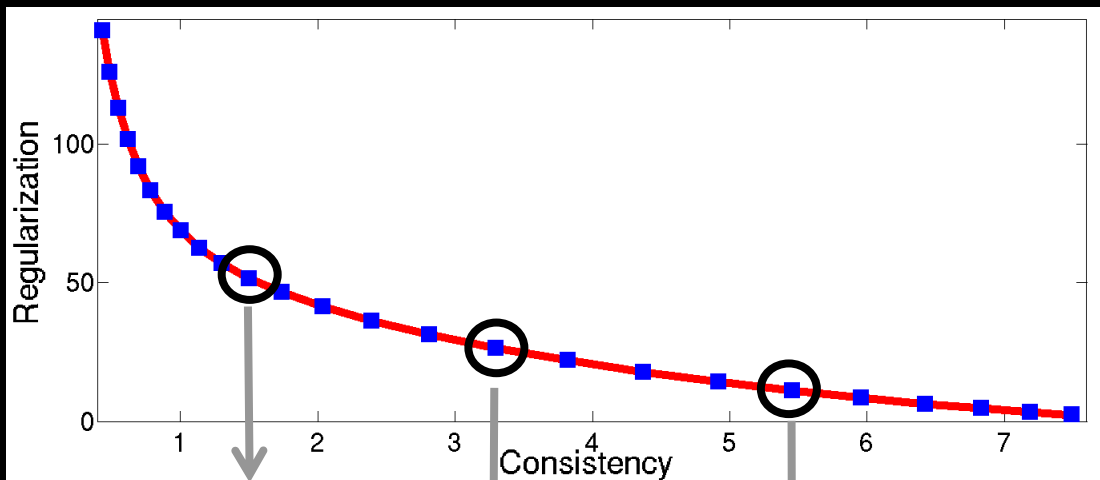
Under-regularized
 $\lambda = 0.001$



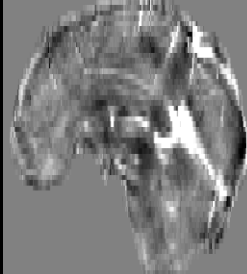
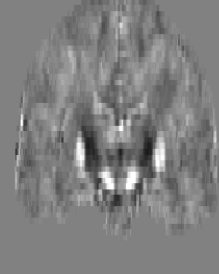
Optimally-regularized
 $\lambda = 0.013$

Tracing the L-curve

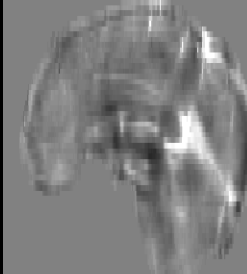
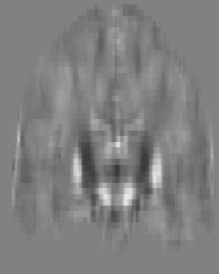
$$\|G\chi\|_2$$



Under-regularized
 $\lambda = 0.001$



Optimally-regularized
 $\lambda = 0.013$



Over-regularized
 $\lambda = 0.091$

$$\|\phi - F^H DF\chi\|_2$$

Conclusion

- Proposed closed form recon for L2-regularized QSM
- 1000-times faster recon compared to Conjugate Gradient solver [1,2]
- Automatic selection for λ feasible with L-curve in a minute
- Software Download:

<http://web.mit.edu/berkin/www/software.html>

Acknowledgments

- Sponsors:

- ❖ MIT-CIMIT Medical Engineering Fellowship
- ❖ Siemens Healthcare
- ❖ Siemens-MIT Alliance

- Grants:

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- ❖ R01EB006847, R01EB007942,
- ❖ R01EB000790, P41RR14075