Optimized CS-Wave imaging with tailored data-sampling and efficient reconstruction

B Bilgic, H Ye, LL Wald, K Setsompop

Martinos Center for Biomedical Imaging, Charlestown, MA, USA
Department of Radiology, Harvard Medical School, Boston, MA, USA

INTERNATIONAL SOCIETY FOR ISMRM MAGNETIC RESONANCE IN MEDICINE
ONE COMMUNITY FOR CLINICIANS AND SCIENTISTS
24th Annual Meeting & Exhibition • 07–13 May 2016
SMRT 25th Annual Meeting • 07–08 May
SINGAPORE
www.ismrm.org • www.smrt.org

Declaration of Financial Interests or Relationships

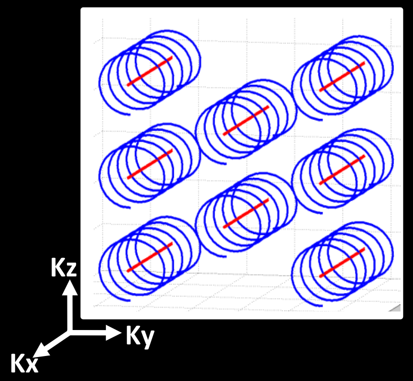
Speaker Name: Berkin Bilgic

I have no financial interests or relationships to disclose with regard to the subject matter of this presentation.

Wave-CAIPI for 3D-GRE

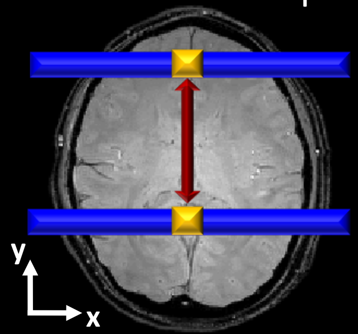
- Wave-CAIPI modifies 3D GRE trajectory to follow a corkscrew along each readout line [1]
- For accelerated acquisitions, this spreads the aliasing in all 3D dimensions to substantially improve parallel imaging
- Acquisition has the same off-resonance characteristic as Normal GRE (voxel shift in readout), and recon is fully Cartesian

Wave-CAIPI trajectory



Normal GRE

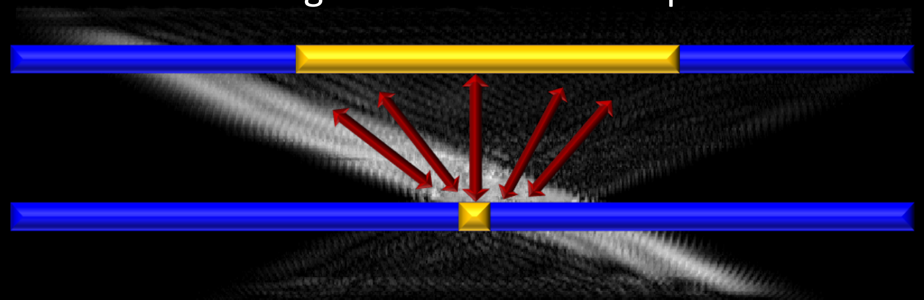
two voxels collapse



R=2 acceleration in Ky

Wave-CAIPI

aliasing voxels are further apart



Aliasing voxels are spread out to increase the variation in coil sensitivity profiles:

Improved G-Factor

[1] B Bilgic, MRM'14

Compressed Sensing Wave

- Recently introduced CS-Wave [1] employed Poisson sampling and Wavelet penalty to combine Compressed Sensing with Wave encoding

- We propose optimized CS-Wave with
  - Efficient ADMM reconstruction
  - Total Variation regularization
  - Tailored data-sampling

- When combined, these double the improvement achieved by the previous CS-Wave

- Providing 20% RMSE reduction over Wave-CAIPI at **15-fold accl**

[1] AT Curtis et al, ISMRM’15

Compressed Sensing Wave

- Recently introduced CS-Wave [1] employed Poisson sampling and Wavelet penalty to combine Compressed Sensing with Wave encoding

- We propose optimized CS-Wave with
  - Efficient ADMM reconstruction
  - Total Variation regularization
  - Tailored data-sampling

- Combining CS-Wave with Simultaneous MultiSlice (SMS) Echo-Shift strategy [2] further increases the acceleration to **30-fold (15×2)**

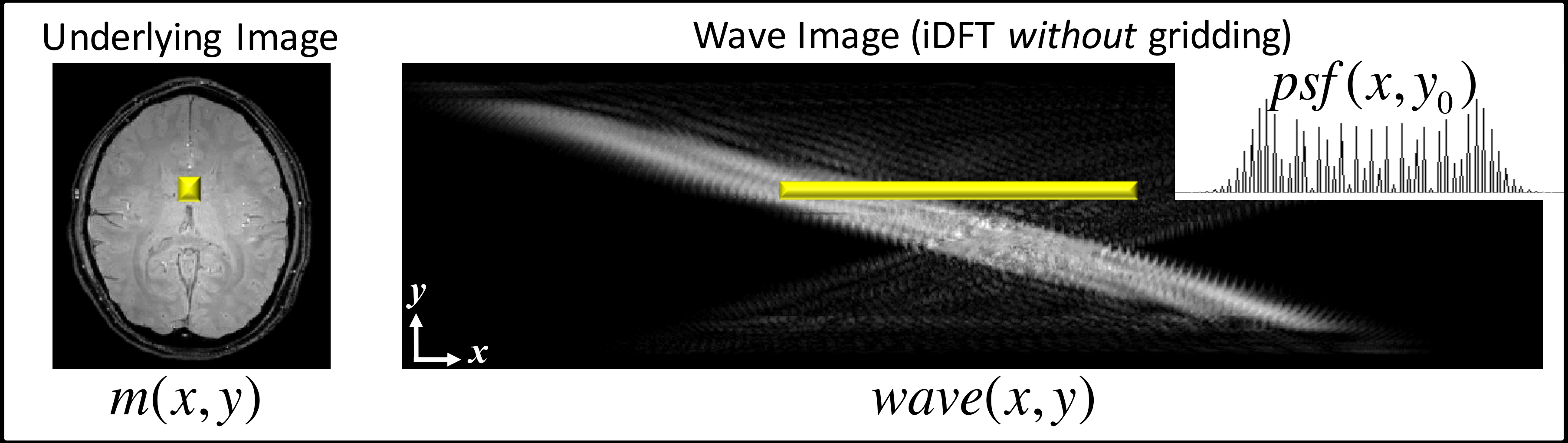
- Enabling Quantitative Susceptibility Mapping (QSM) from 3 head orientations at long TE and 1.5 mm iso in **72 sec (24 sec / orientation)**

[1] AT Curtis et al, ISMRM'15
[2] H Ye et al ISMRM'16 p3246

Wave Recon: Forward Model

- Despite following a non-Cartesian trajectory, Wave encoding can be expressed in Cartesian space through point spread function (psf):

$$wave(x,y) = \mathrm{psf}(x,y) \otimes m(x,y)$$

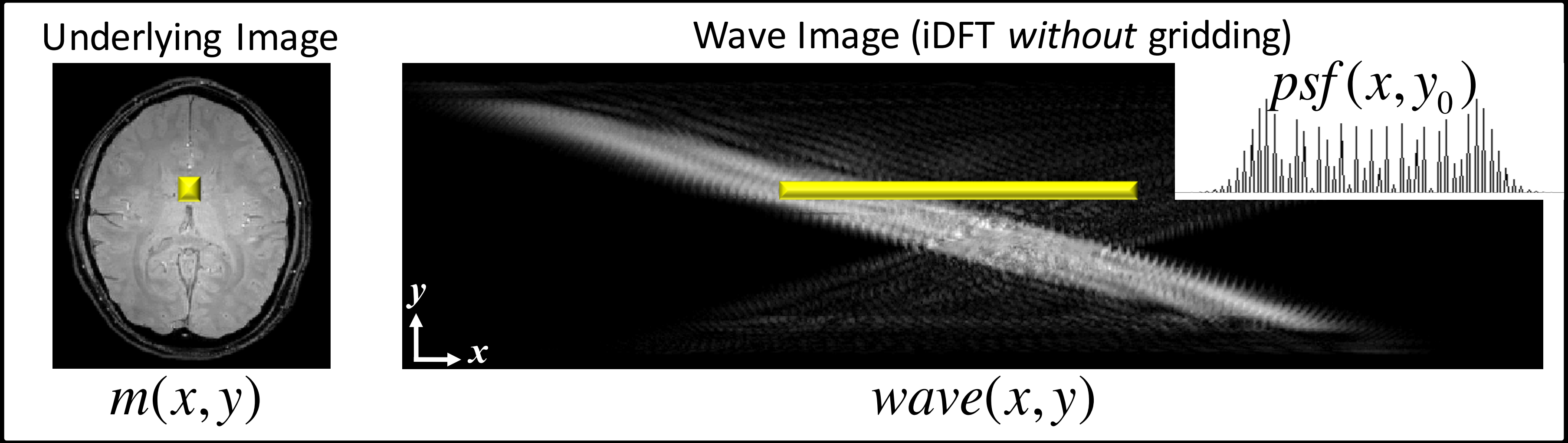


Wave Recon: Forward Model

- Despite following a non-Cartesian trajectory, Wave encoding can be expressed in Cartesian space through point spread function (psf):

$$wave(x,y) = \mathrm{F}_x^{\mathrm{H}} \cdot \mathrm{Psf}(k_x, y) \cdot \mathrm{F}_x \cdot m(x,y)$$

No need for gridding, simple DFT



Wave Recon: Forward Model

- Extend to 3D using both G_y and G_z sinusoidal gradient waveforms:

$$wave(x,y,z) = \mathrm{F}_{\mathrm{x}}^{\mathrm{H}} \cdot \mathrm{Psf}(k_x, y, z) \cdot \mathrm{F}_{\mathrm{x}} \cdot m(x,y,z)$$

Wave Recon: Forward Model

- And go to 3D k-space by applying DFT to both sides:

$$\underline{\mathrm{F}_{\mathrm{xyz}}} \cdot wave(x,y,z) = \underline{\mathrm{F}_{\mathrm{yz}}} \cdot \mathrm{Psf}(k_x,y,z) \cdot \mathrm{F}_{\mathrm{x}} \cdot m(x,y,z)$$

Wave Recon: Forward Model

- And go to 3D k-space by applying DFT to both sides:

$$\underline{k} = \mathrm{F}_{\mathrm{yz}} \cdot \mathrm{Psf} \cdot \mathrm{F}_{\mathrm{x}} \cdot m$$

Wave Recon: Forward Model

- Include coil sensitivities and undersampling mask to obtain the forward SENSE model

$$k = \underline{\mathrm{M}} \cdot \mathrm{F}_{\mathrm{yz}} \cdot \mathrm{Psf} \cdot \mathrm{F}_{\mathrm{x}} \cdot \underline{\mathrm{S}} \cdot m$$

Wave Recon: Forward Model

- Include coil sensitivities and undersampling mask to obtain the forward SENSE model

$$k = \mathrm{M} \cdot \underline{\mathrm{E}} \cdot m$$

$$\text{encoding} \quad \mathrm{E} = \mathrm{F}_{\mathrm{yz}} \cdot \mathrm{Psf} \cdot \mathrm{F}_{\mathrm{x}} \cdot \mathrm{S}$$

Efficient CS-Wave Recon

- Regularized least squares to incorporate Compressed Sensing:

$$1/2\left\| k - \mathrm{M} \cdot \mathrm{E} \cdot m \right\|_2^2 \;+\; \lambda \left\| \mathrm{R} \cdot m \right\|_1$$

Efficient CS-Wave Recon

- For efficient optimization, we adopt ADMM [1,2] and introduce auxiliary variables for data consistency and regularization terms:

$$1/2\left\|k - \mathrm{M}\cdot\mathrm{E}\cdot m\right\|_2^2 \;+\; \lambda\left\|\mathrm{R}\cdot m\right\|_1$$

$$c = \mathrm{E}\cdot m \qquad r = \mathrm{R}\cdot m$$

- This allows us to separate the difficult 3D optimization problem into smaller subproblems that are solved in closed form for c and r

[1] S Boyd et al, Found Trends Mach Learn'10
[2] T Goldstein et al, SIAM J Imaging Sci'09

Efficient CS-Wave Recon

- For efficient optimization, we adopt ADMM [1,2] and introduce auxiliary variables for data consistency and regularization terms:

$$1/2\|k - \mathrm{M}\cdot\mathrm{E}\cdot m\|_2^2 \; + \; \lambda\|\mathrm{R}\cdot m\|_1$$

$$c = \mathrm{E}\cdot m \qquad r = \mathrm{R}\cdot m$$

- And the image update is found by a simple linear combination of data consistency and regularization

$$(\alpha\cdot \mathrm{S}^2 + \beta\cdot \mathrm{R}^2)\cdot m = \alpha\cdot \mathrm{E}^H(c - \underline{d_c}) + \beta\cdot \mathrm{R}^H(r - \underline{d_r})$$

d_c & d_r: dual variables

α & β: Lagrange parameters

[1] S Boyd et al, Found Trends Mach Learn'10
[2] T Goldstein et al, SIAM J Imaging Sci'09

Efficient CS-Wave Recon

- For efficient optimization, we adopt ADMM [1,2] and introduce auxiliary variables for data consistency and regularization terms:

$$1/2\left\|k - \mathrm{M}\cdot\mathrm{E}\cdot m\right\|_2^2 + \lambda\left\|\mathrm{R}\cdot m\right\|_1$$

$$c = \mathrm{E}\cdot m \qquad r = \mathrm{R}\cdot m$$

- And the image update is found by a simple linear combination of data consistency and regularization: closed-form for Wavelet

$$\underline{(\alpha\cdot\mathrm{S}^2 + \beta\cdot\mathrm{R}^2)}\cdot m = \alpha\cdot\mathrm{E}^H(c - d_c) + \beta\cdot\mathrm{R}^H(r - d_r)$$

$\mathrm{R}^2 = \mathrm{I}$ for Wavelet

$\mathrm{S}^2 =$ SoS of sensitivities

[1] S Boyd et al, Found Trends Mach Learn'10
[2] T Goldstein et al, SIAM J Imaging Sci'09

Efficient CS-Wave Recon

- For efficient optimization, we adopt ADMM [1,2] and introduce auxiliary variables for data consistency and regularization terms:

$$1/2\left\|k - \mathrm{M}\cdot\mathrm{E}\cdot m\right\|_2^2 + \lambda\left\|\mathrm{R}\cdot m\right\|_1$$

$$c = \mathrm{E}\cdot m \qquad r = \mathrm{R}\cdot m$$

- And the image update is found by a simple linear combination of data consistency and regularization: closed-form for Wavelet

$$m = (\alpha\cdot\mathrm{S}^2 + \beta\cdot\mathrm{I})^{-1}\cdot\left[\alpha\cdot\mathrm{E}^H(c - d_c) + \beta\cdot\mathrm{R}^H(r - d_r)\right]$$

[1] S Boyd et al, Found Trends Mach Learn'10
[2] T Goldstein et al, SIAM J Imaging Sci'09

Efficient CS-Wave Recon

- For efficient optimization, we adopt ADMM [1,2] and introduce auxiliary variables for data consistency and regularization terms:

$$1/2\|k - \mathrm{M}\cdot\mathrm{E}\cdot m\|_2^2 + \lambda\|\mathrm{R}\cdot m\|_1$$

$$c = \mathrm{E}\cdot m \qquad r = \mathrm{R}\cdot m$$

- And the image update is found by a simple linear combination of data consistency and regularization: Preconditioned Conjugate Gradient for Total Variation

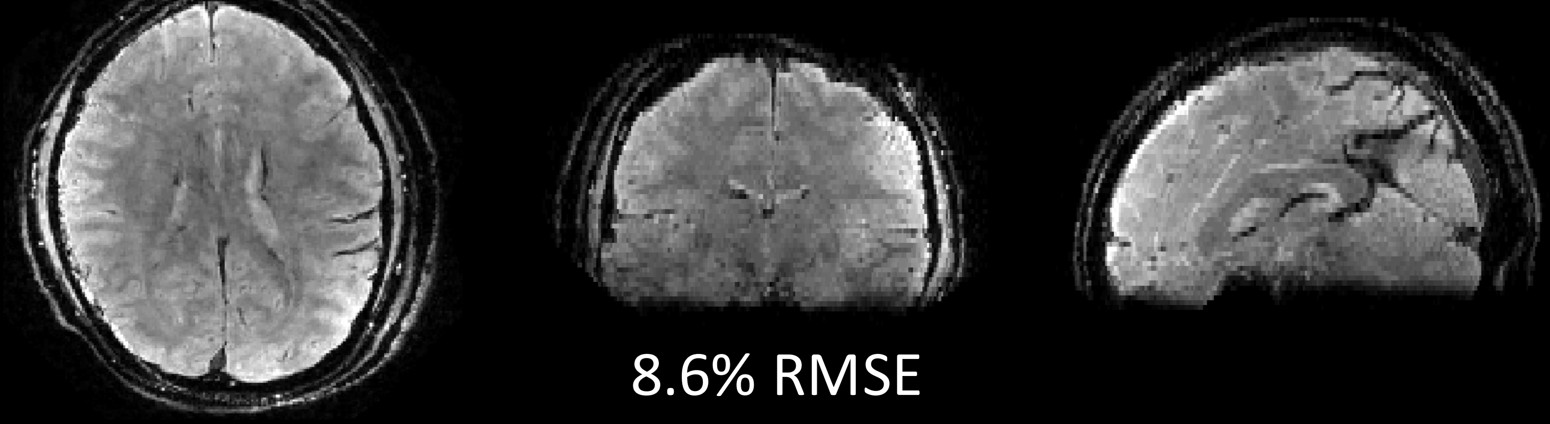
$$\underline{(\alpha\cdot\mathrm{S}^2 + \beta\cdot\mathrm{R}^2)}\cdot m = \alpha\cdot\mathrm{E}^H(c - d_c) + \beta\cdot\mathrm{R}^H(r - d_r)$$

$$diag(\mathrm{R}^2) = 6\cdot\mathrm{I} \quad \text{for TV since Laplacian}$$

[1] S Boyd et al, Found Trends Mach Learn'10
[2] T Goldstein et al, SIAM J Imaging Sci'09

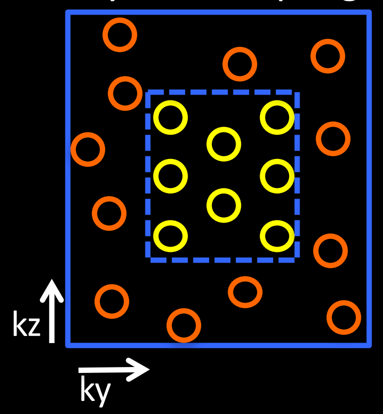
Wave encoding with R=15 accl @ 7T

Proposed: CS-Wave



8.6% RMSE

hybrid sampling

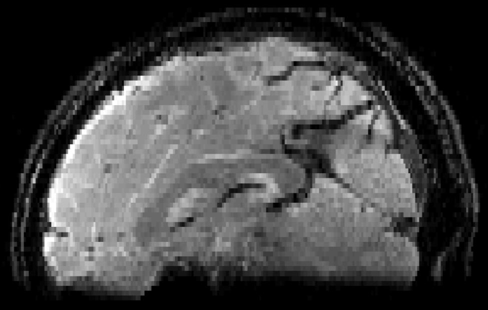


- Res = 1x1x2 mm^3
- FOV = 224x222x120 mm^3 tight
- TE/TR = 10.9/27 ms
- ESPIRiT [1] sensitivities from 16x16x16 points
- Hybrid sampling [2]: Center 25% w/ R=3x3 Caipi; Outer 75% w/ VD Poisson } Total R=15-fold
- **T_{acq} = 25 sec**

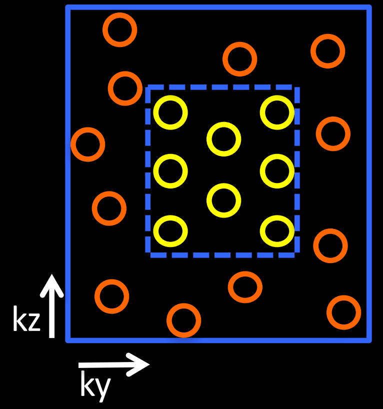
[1] M Uecker et al MRM'14
[2] K Sung et al MRM'13

Wave encoding with R=15 accl @ 7T

Proposed: CS-Wave

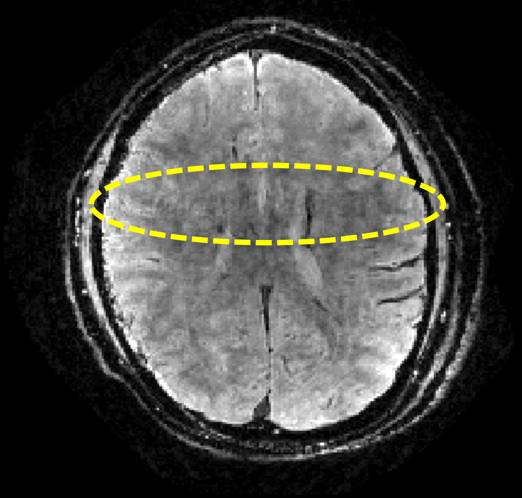


hybrid sampling

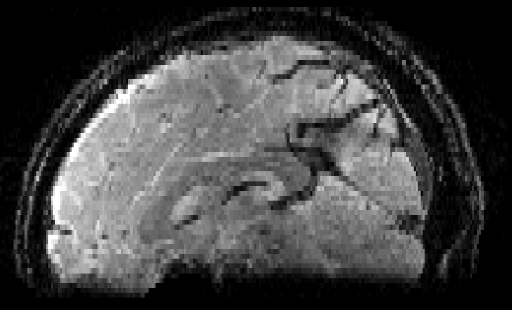


8.6% RMSE

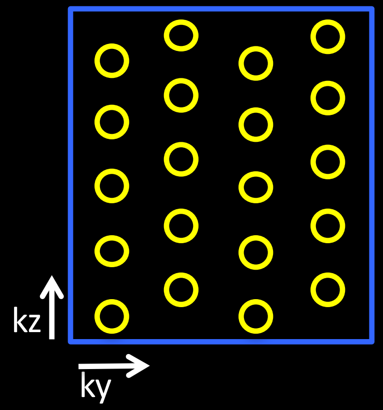
Recon 8.4 min



Wave-CAIPI



caipi sampling

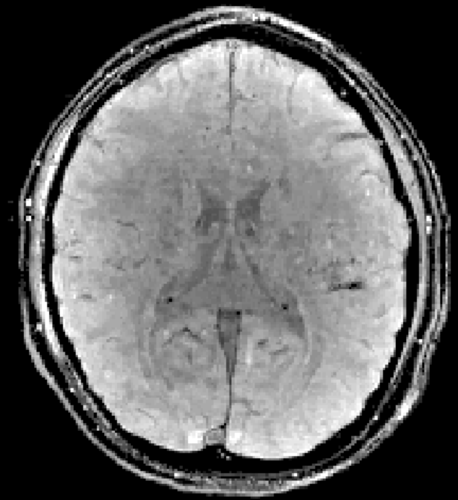


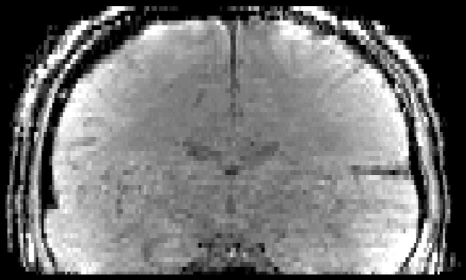
10.2% RMSE

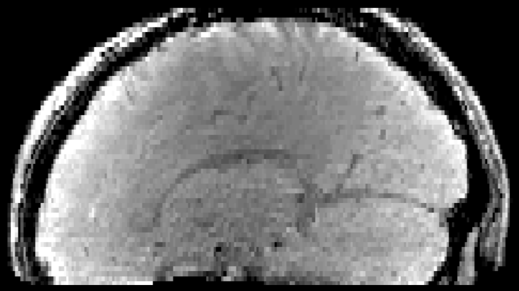
Recon 1.8 min

Wave encoding with R=15 accl @ 3T

Proposed: CS-Wave

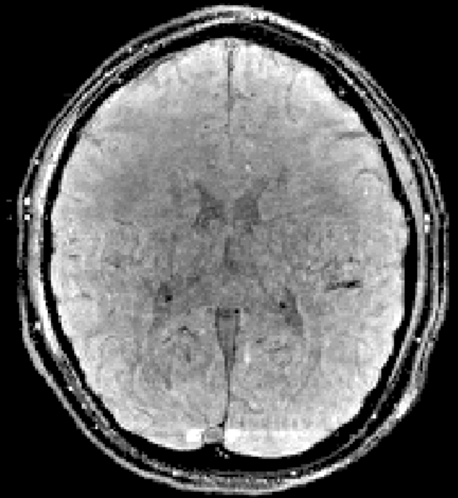


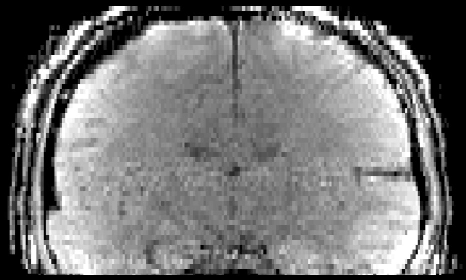




7.4% RMSE

Wave-CAIPI





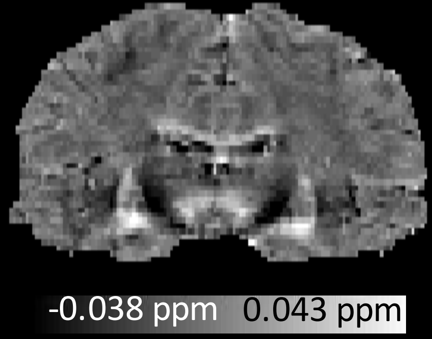
8.9% RMSE

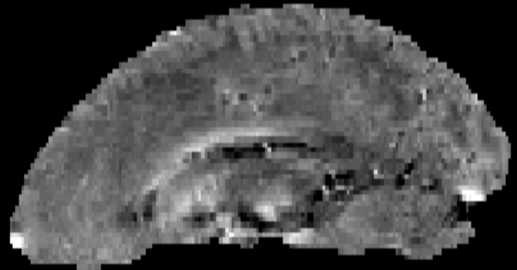
- **T_{acq} = 24 sec**
- TE/TR = 13.3/26 ms

Phase & QSM with R=15 accl @ 7T

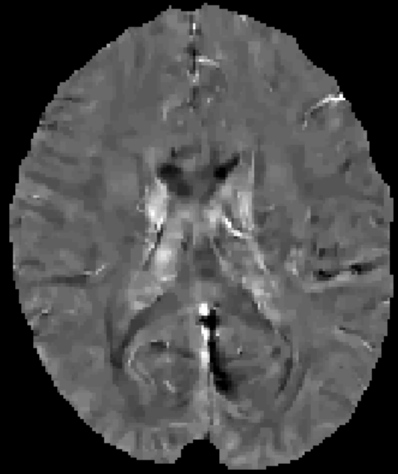
Proposed: CS-Wave

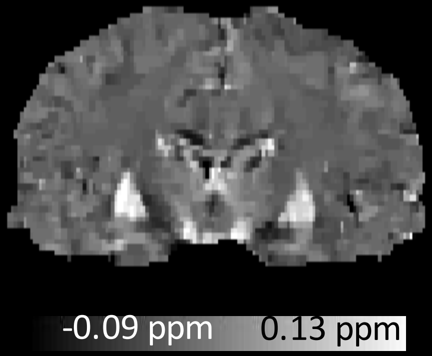
<u>Tissue Phase</u>
<u>V-SHARP [1,2]</u>

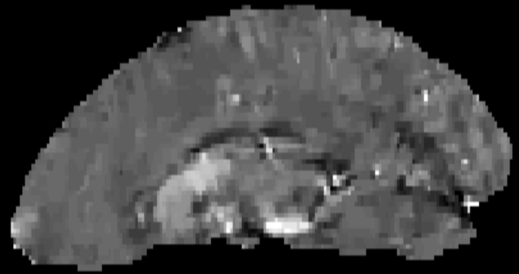




<u>Susceptibility Map</u>
<u>Single-Step TGV [3]</u>



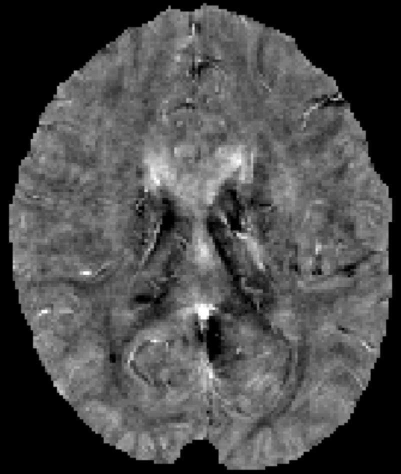




[3] I Chatnuntawech et al ISMRM'16, p.869
Thu 10:30 Sparse Road to Quantitative Imaging

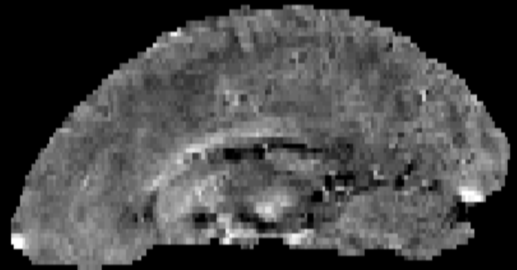
Phase & QSM with R=15 accl @ 7T

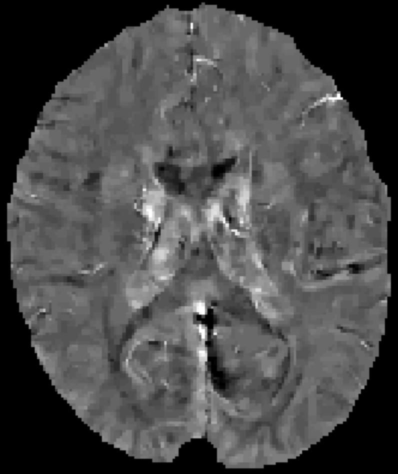
Wave-CAIPI



Tissue Phase

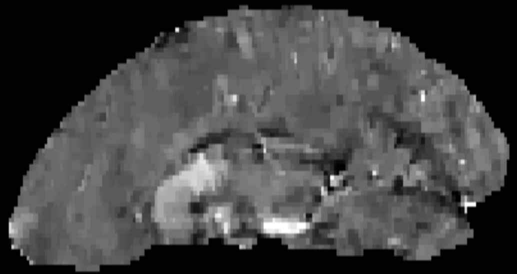
-0.038 ppm 0.043 ppm





Susceptibility Map
Single-Step TGV [3]

-0.09 ppm 0.13 ppm

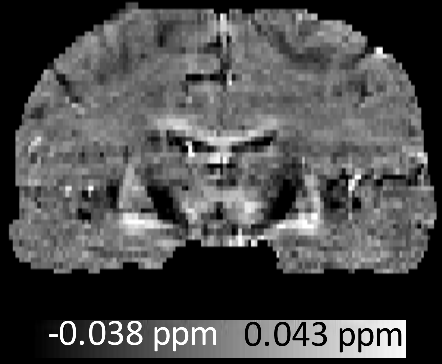


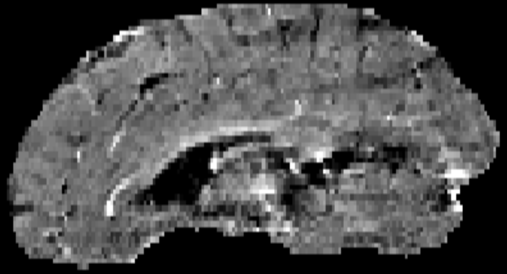
[3] I Chatnuntawech et al ISMRM'16, p.869
Thu 10:30 Sparse Road to Quantitative Imaging

Phase & QSM with R=15 accl @ 3T

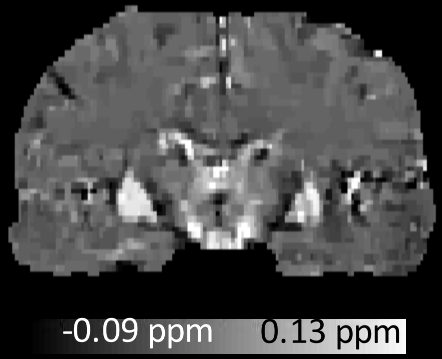
Proposed: CS-Wave

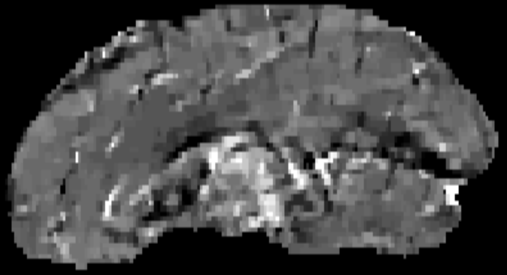
Tissue Phase





Susceptibility Map
Single-Step TGV [3]

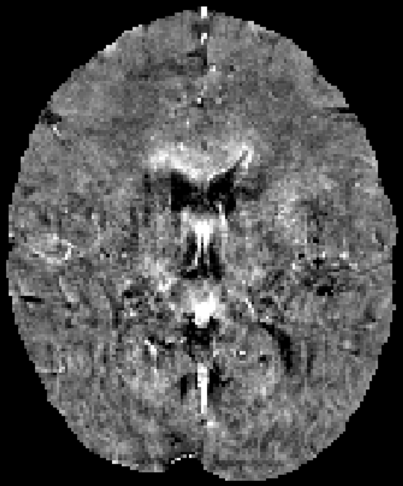




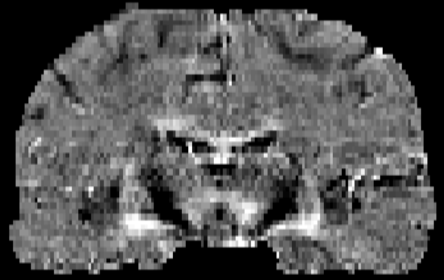
[3] I Chatnuntawech et al ISMRM'16, p.869
Thu 10:30 Sparse Road to Quantitative Imaging

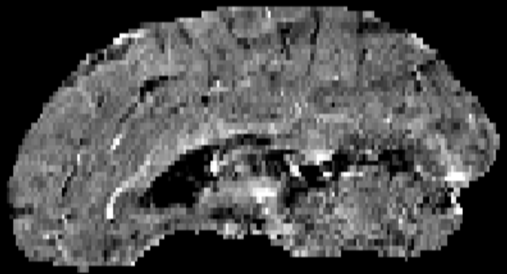
Phase & QSM with R=15 accl @ 3T

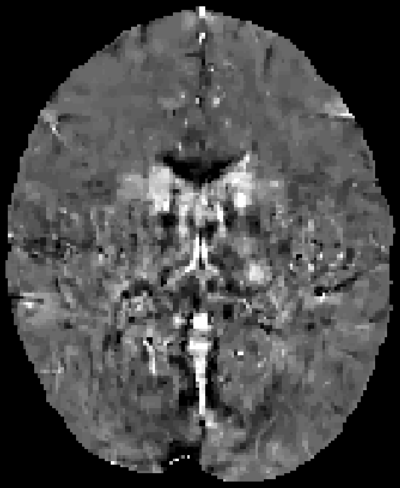
Wave-CAIPI



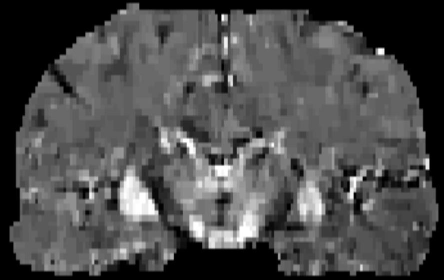
Tissue Phase

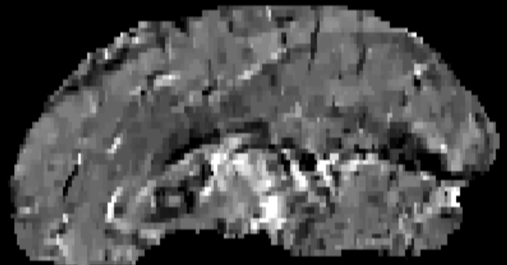






Susceptibility Map
Single-Step TGV [3]





[3] I Chatnuntawech et al ISMRM'16, p.869
Thu 10:30 Sparse Road to Quantitative Imaging

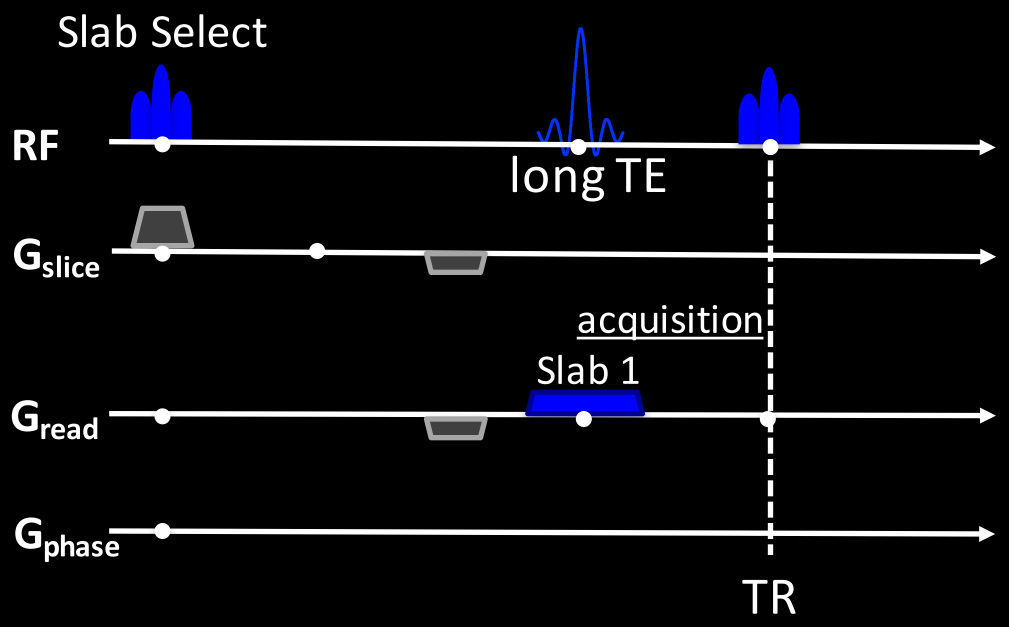
Echo-Shift

- For SWI and QSM, long TE is desired to build up phase and T_2^* contrast, which leads to long TR and acquisition time
- Echo-shift exploits the unused sequence time and interleaves multiple echos within a single TR and improves efficiency in 2D [1] or 3D [2] acquisitions
- Echo-shift has also been used for fMRI (PRESTO) [3], and combined with (SMS) [4] for further acceleration for 2D imaging

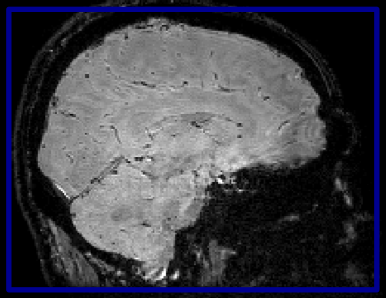
[1] CTW Moonen et al MRM'92
[2] YJ Ma et al MRM'15
[3] G Liu et al MRM'93
[4] R Boyacioğlu et al SMS Workshop'15

Multi-Slab Echo-Shift for 3D imaging

- Conventional 3D-GRE: substantial unused time due to late TR

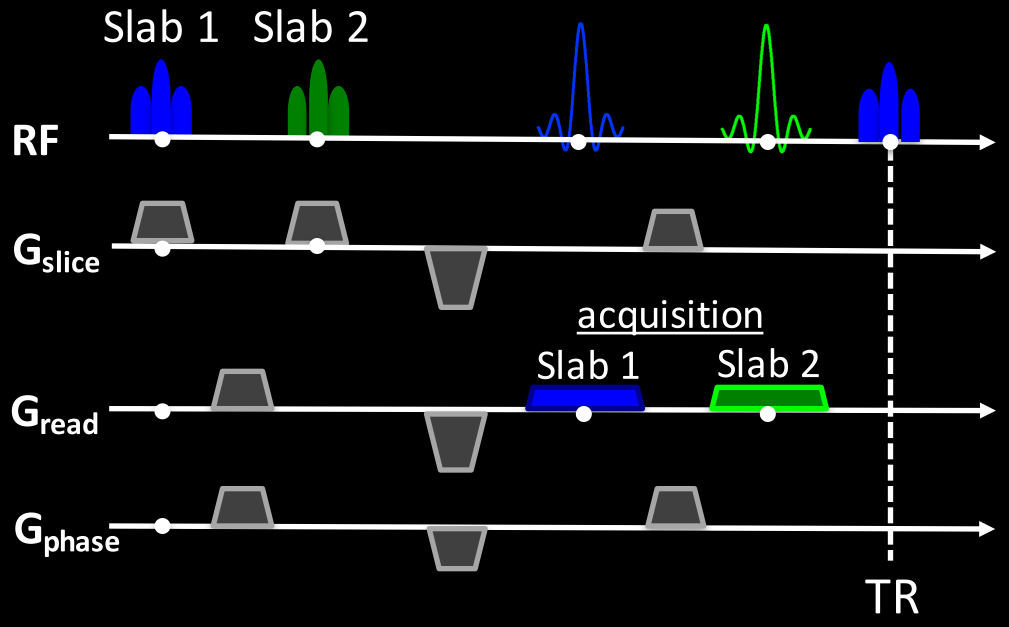


Conventional
3D encoding

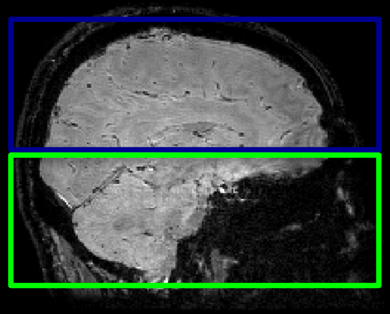


Multi-Slab Echo-Shift for 3D imaging

- Multi-Slab Echo-Shift: add a second readout and crusher gradients for faster encoding



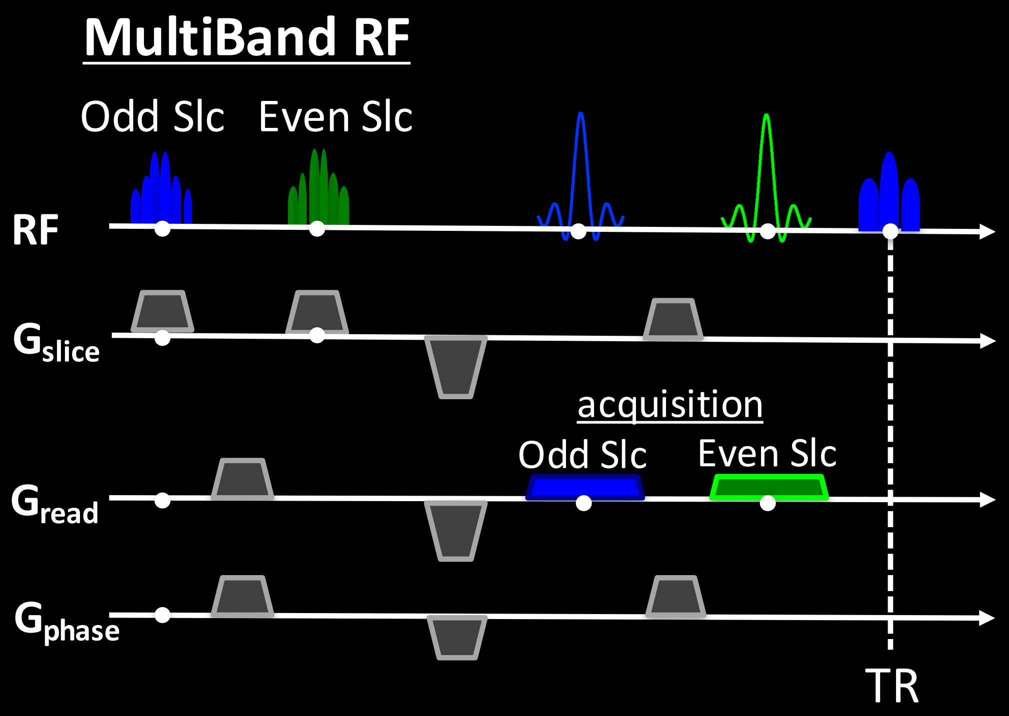
Multi-Slab
Echo-Shift



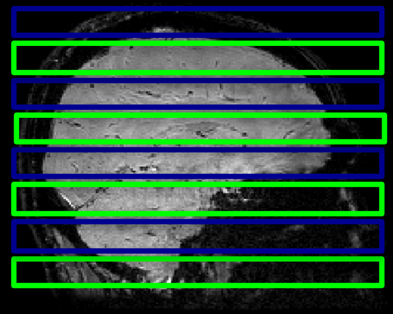
- Slab boundary artifact
- Acceleration in head-foot more difficult since distance between aliasing voxels reduced by half

SMS Echo-Shift for 3D imaging

- SMS Echo-Shift [1]: excite and encode comb slice groups

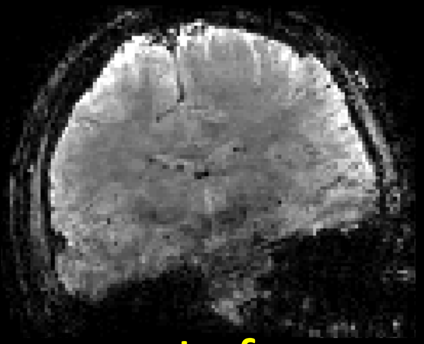


SMS
Echo-Shift

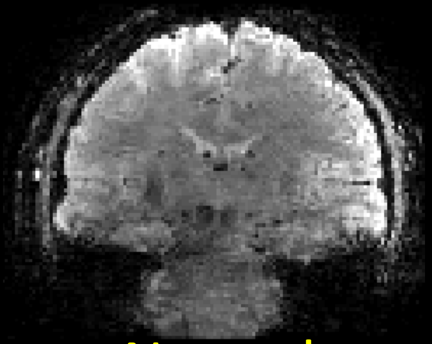


[1] H Ye et al ISMRM’16 p3246

Echo-Shift CS-Wave with R=15×2 accl @ 3T



Left

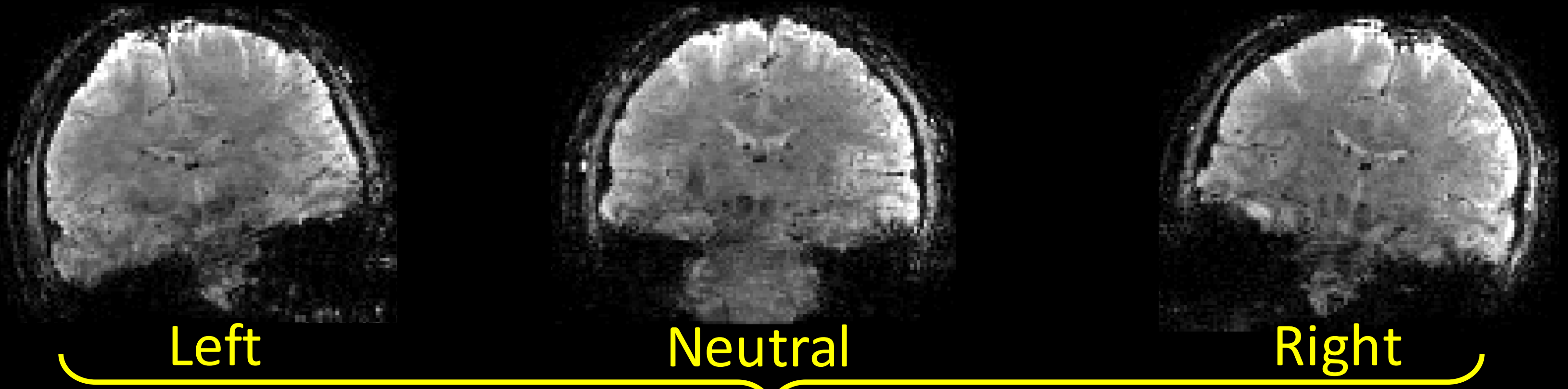


Neutral

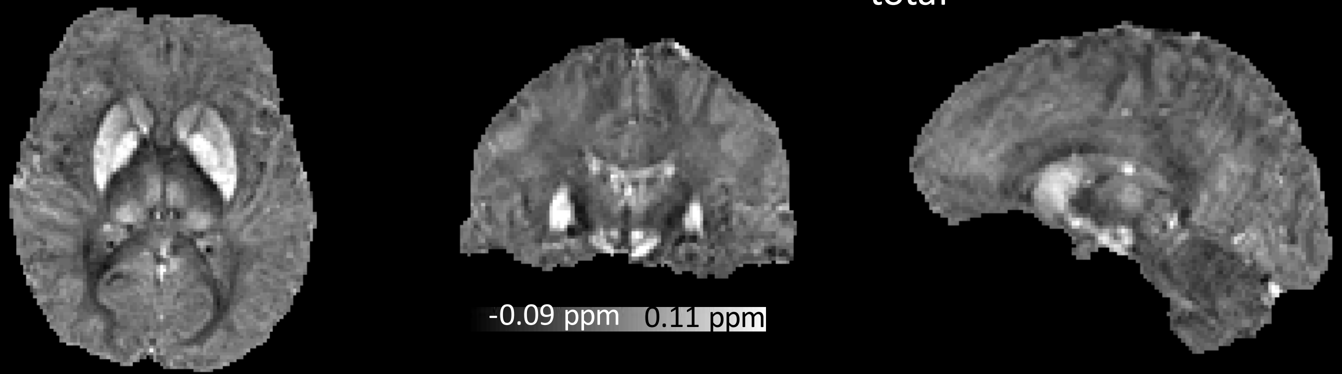
Right

- 1.5 mm iso
- Long TE = 35 ms (TR = 47 ms)
- **T_{acq} = 24 sec**

Echo-Shift CS-Wave with R=15×2 accl @ 3T



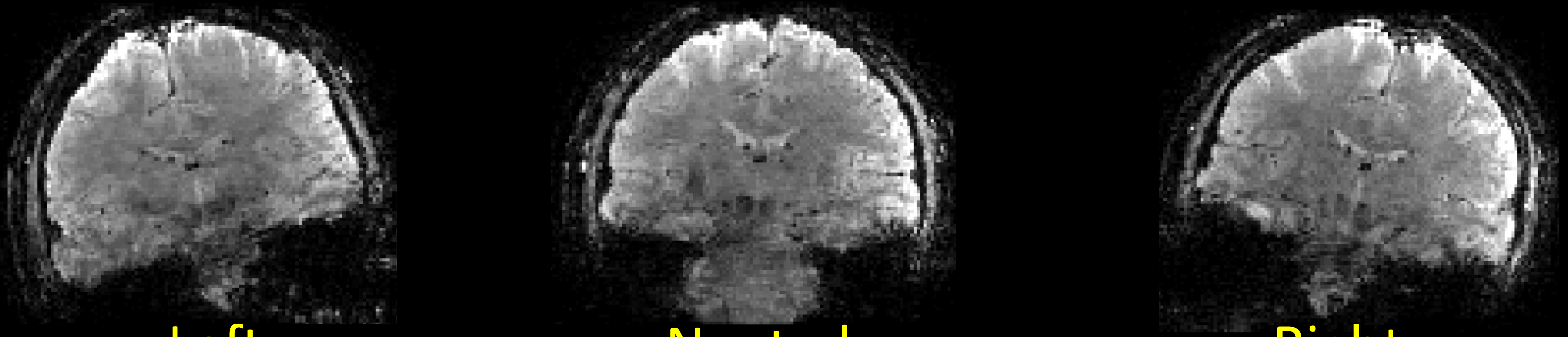
QSM from 3 orientations: T_{total} = 72sec



- Combine information from 3 head orientations to solve QSM inverse problem [1]

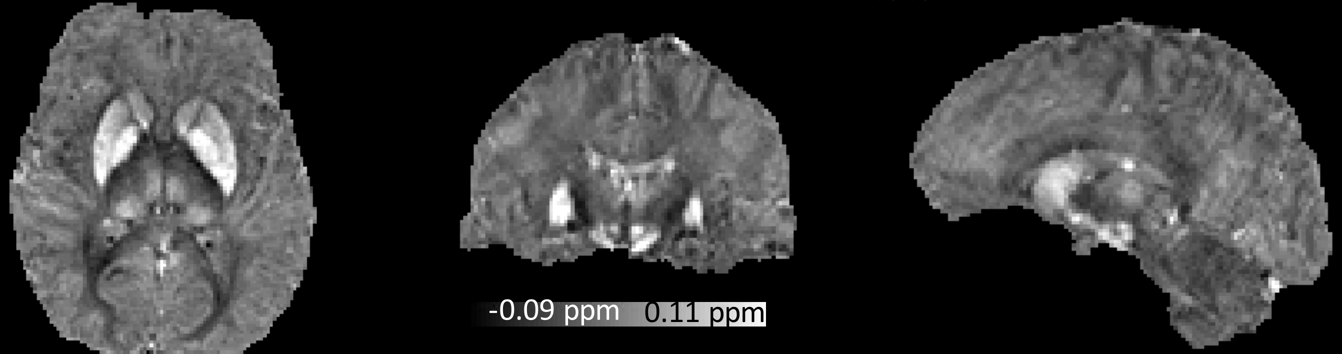
[1] T Liu et al MRM’09

Echo-Shift CS-Wave with R=15×2 accl @ 3T

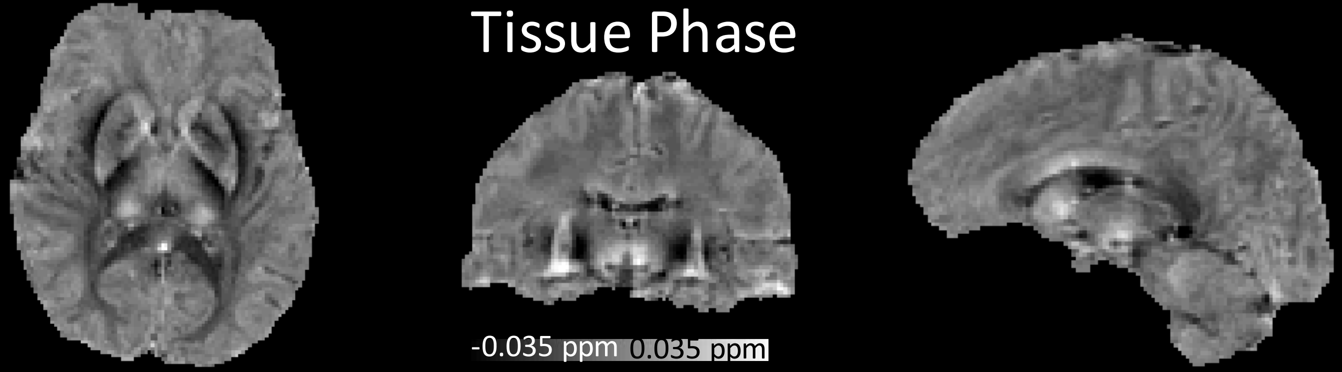


Left Neutral Right

QSM from 3 orientations: T_{total} = 72sec



Tissue Phase



Conclusion

- We proposed optimized CS-Wave with efficient reconstruction and tailored data-sampling
- SMS Echo-Shift strategy utilizes the unused sequence time for extra encoding
- Combining CS-Wave with SMS Echo-Shift permits **30-fold (15×2)** acceleration
- This enables rapid SWI and QSM acquisition at long TE required for optimal contrast
- Questions / Comments:

berkin@nmr.mgh.harvard.edu

- Support: NIH R24MH106096, R01EB020613, R01EB017337, U01HD087211