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ISMRM 2025
MR Artifacts Game Show

Classic Artifacts in Radial MRI and The Semi-convergence Behavior of CG-SENSE

Hung Do, PhD MSEE
Canon Medical Systems USA

Declaration of Financial Interests or Relationships

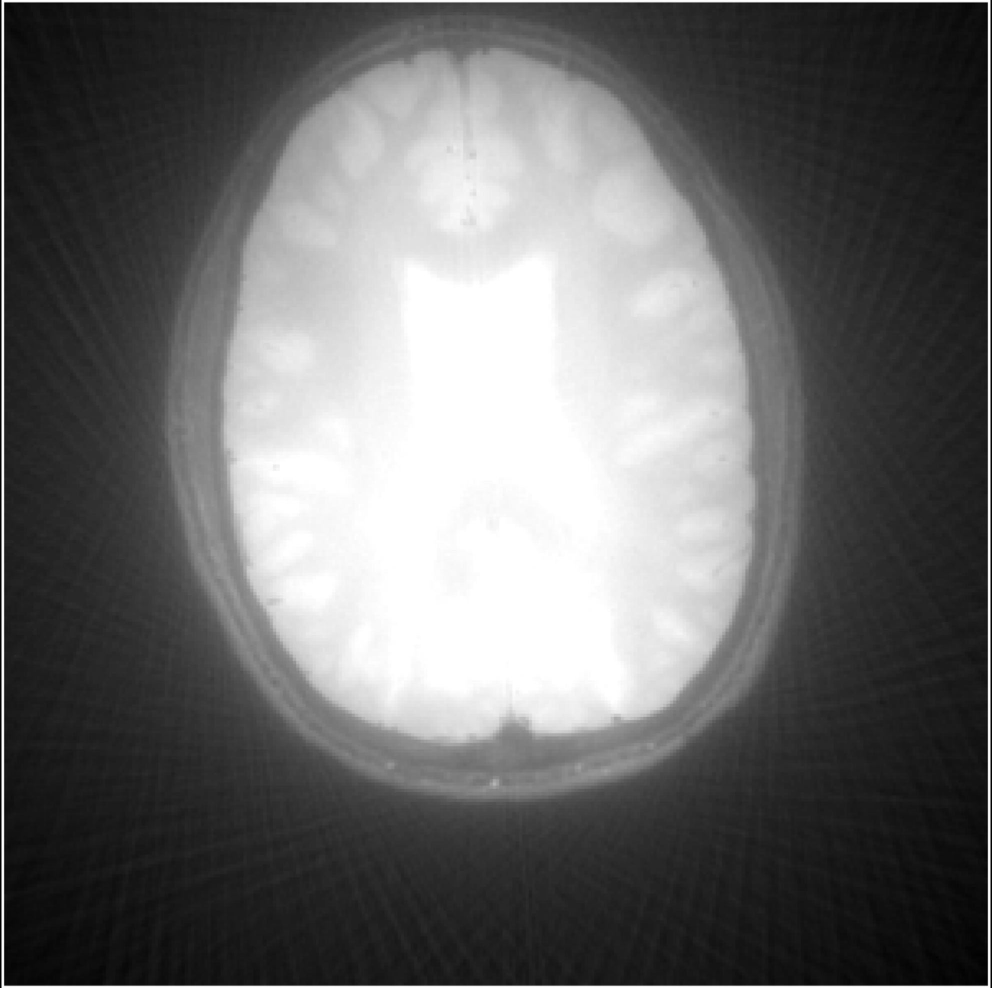
Speaker Name: **Hung Do, PhD MSEE**

I have the following financial interest or relationship to disclose with regard to the subject matter of this presentation:

Company Name: **Canon Medical Systems USA**
Type of Relationship: **Employee**

The *halo* artifact!

Digi Venkat, Wikipedia.org

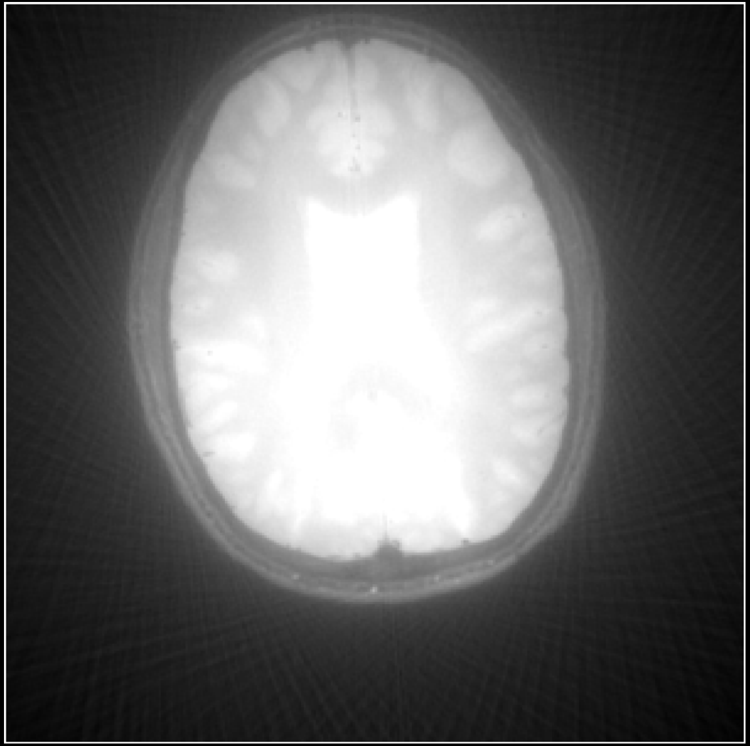


Images from: Hung Do, Canon Medical USA

What causes the *halo* artifact?

A. Corrupted low-frequency k-space
B. Corrupted high-frequency k-space
C. Forget to apply intensity compensation
D. Forget to apply density compensation

2D single-slice radial imaging with gridding reconstruction



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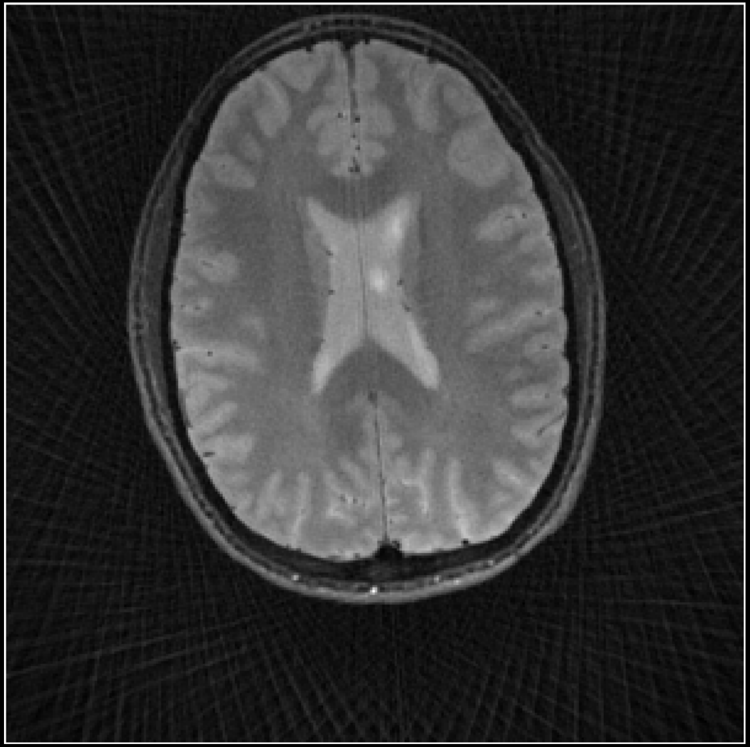
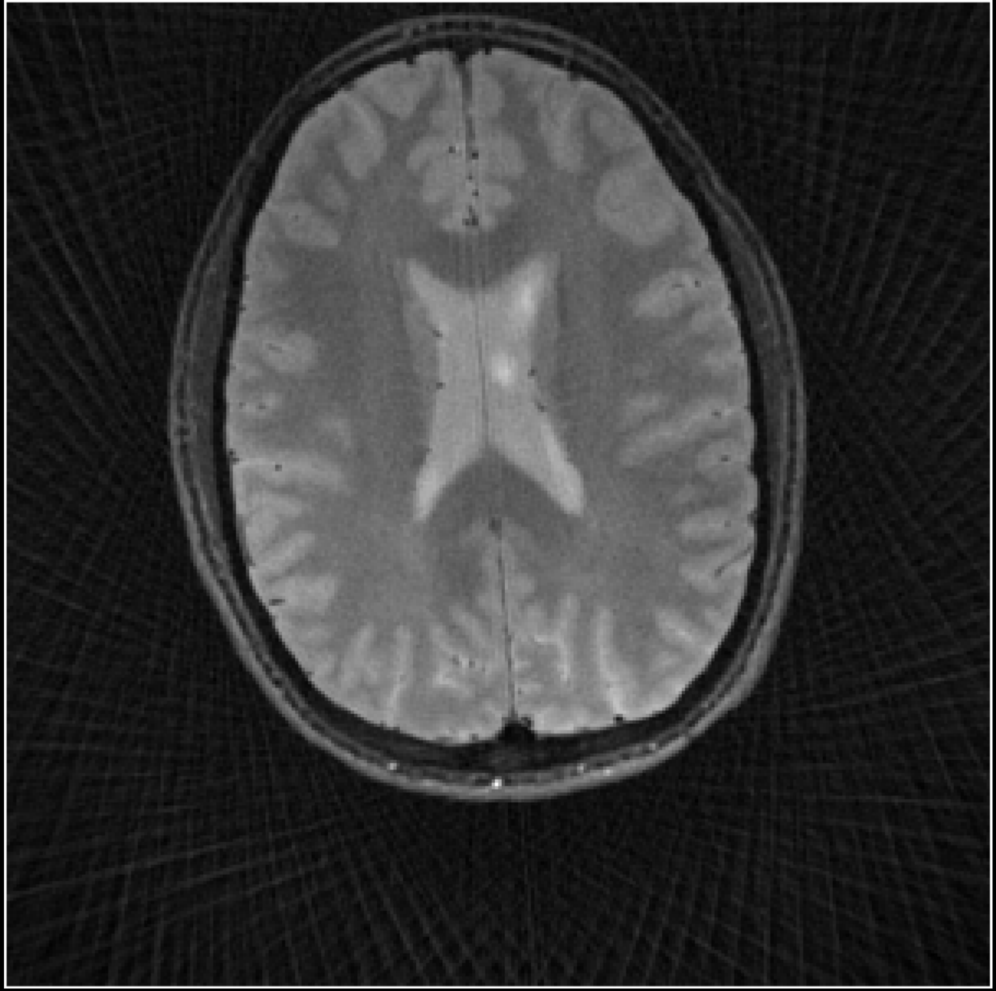


Images from: Hung Do, Canon Medical USA

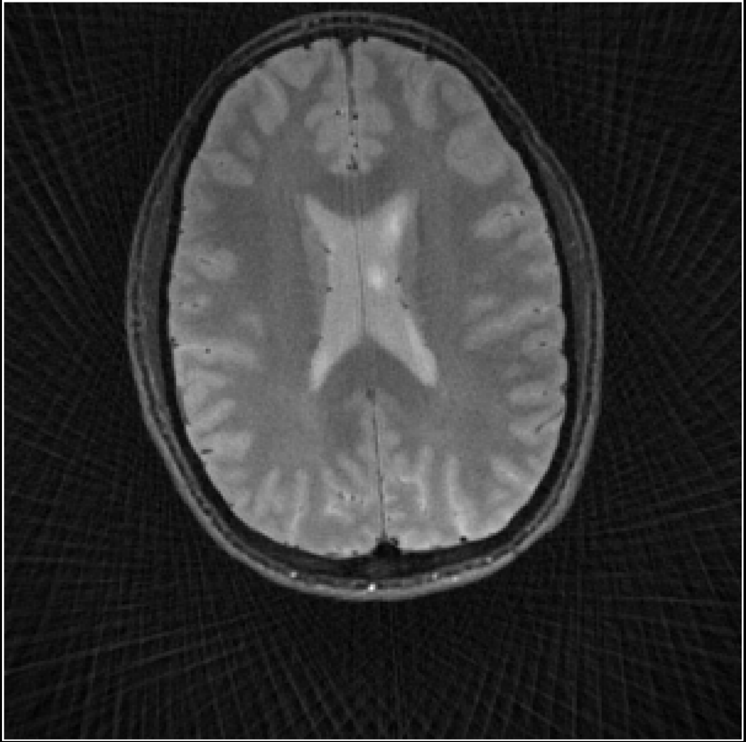
The streaking artifact!



Images from: Hung Do, Canon Medical USA

What causes the *streaking* artifact?

A. Head rotating motions
B. Over-sampled k-space center
C. Under-sampled k-space data
D. Gridding kernel is too narrow



2D single-slice radial imaging with gridding reconstruction

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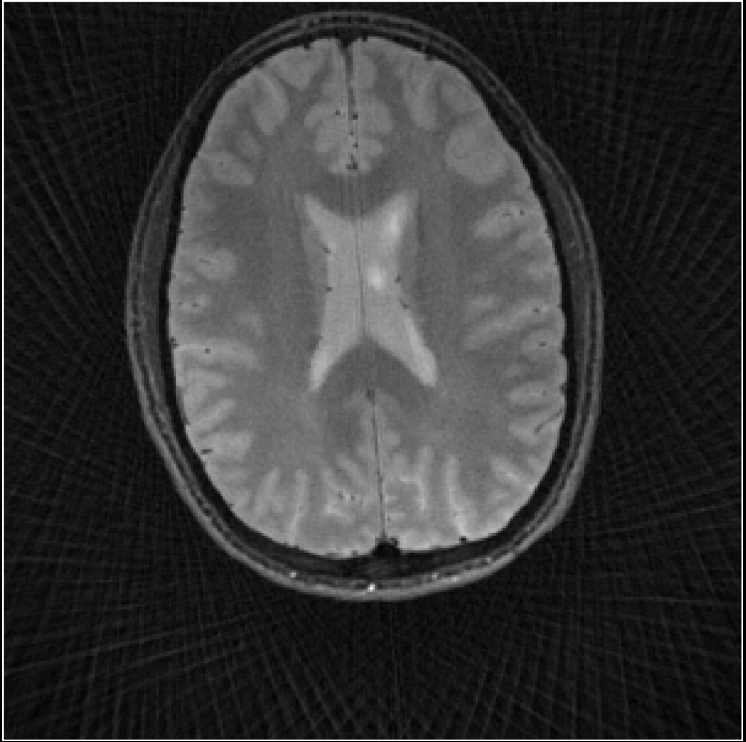
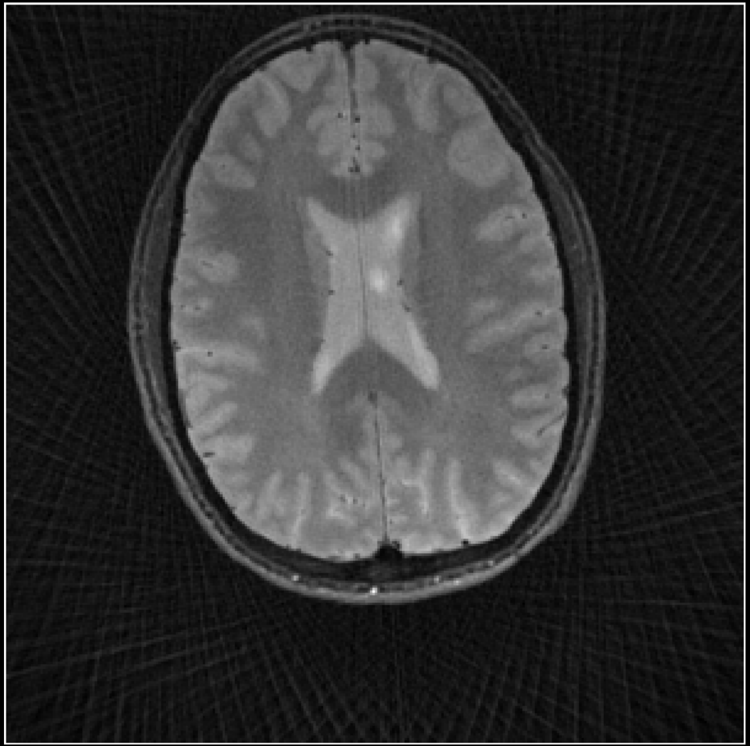


Images from: Hung Do, Canon Medical USA

How can the *streaking* artifact be resolved?

A. Use SENSE (Sensitivity encoding)
B. Use CG-SENSE (Conjugate Gradient SENSE)
C. Use GRAPPA (Generalized Auto calibrating Partial Parallel Acquisition)
D. Use NuFFT (Non-uniform Fast Fourier Transform)



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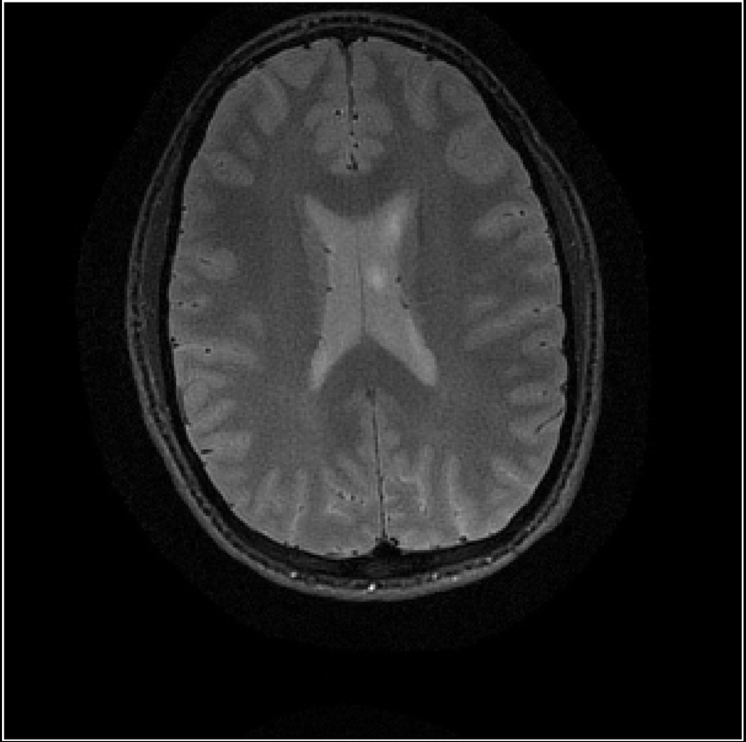


Images from: Hung Do, Canon Medical USA

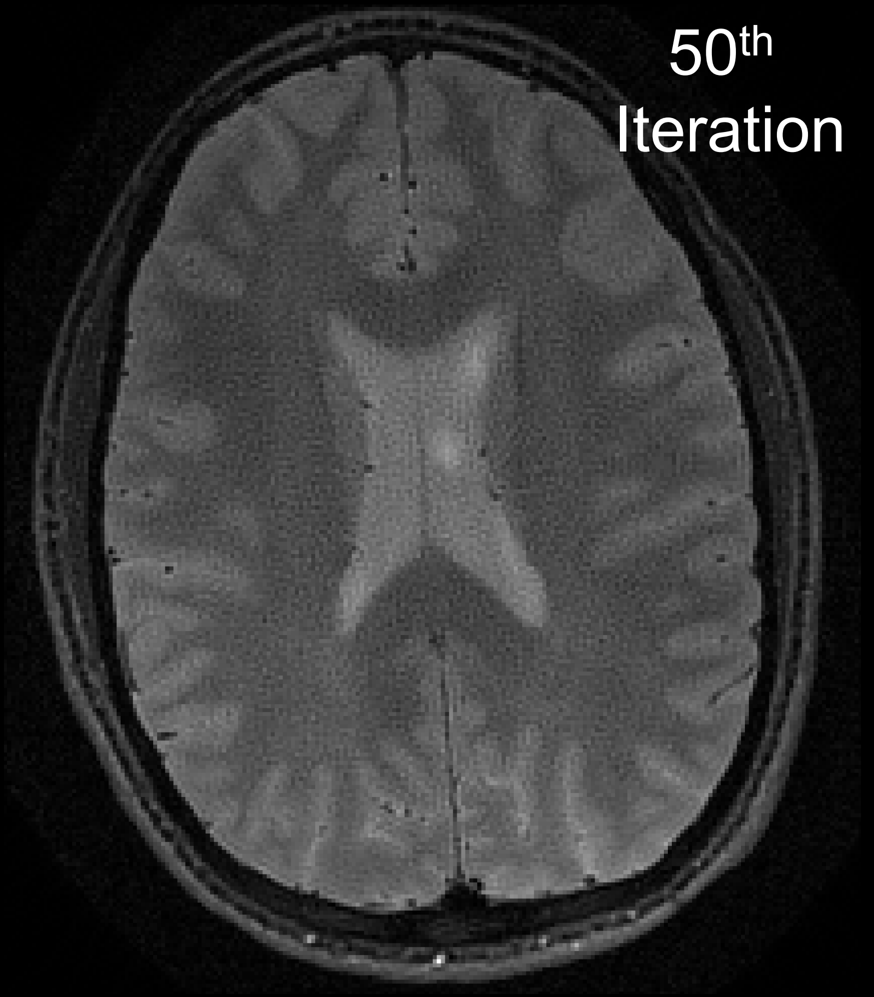
Bonus: Challenging Artifact

The Semi-convergence Behavior of CG-SENSE

What is the Artifact?

A. Remnants of streaking artifacts
B. Over-suppressed background noise
C. Noise amplification
D. Under smoothing

CG-SENSE Recon in action!



50th Iteration

Images from: Hung Do, Canon Medical USA

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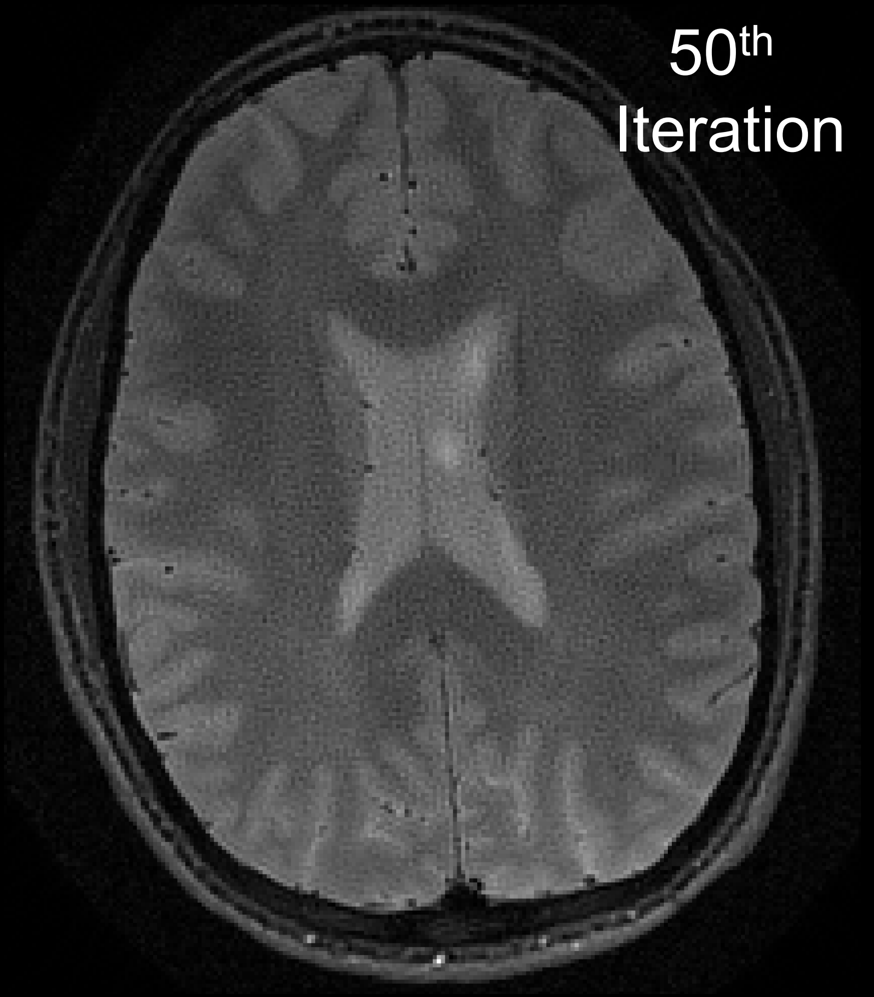
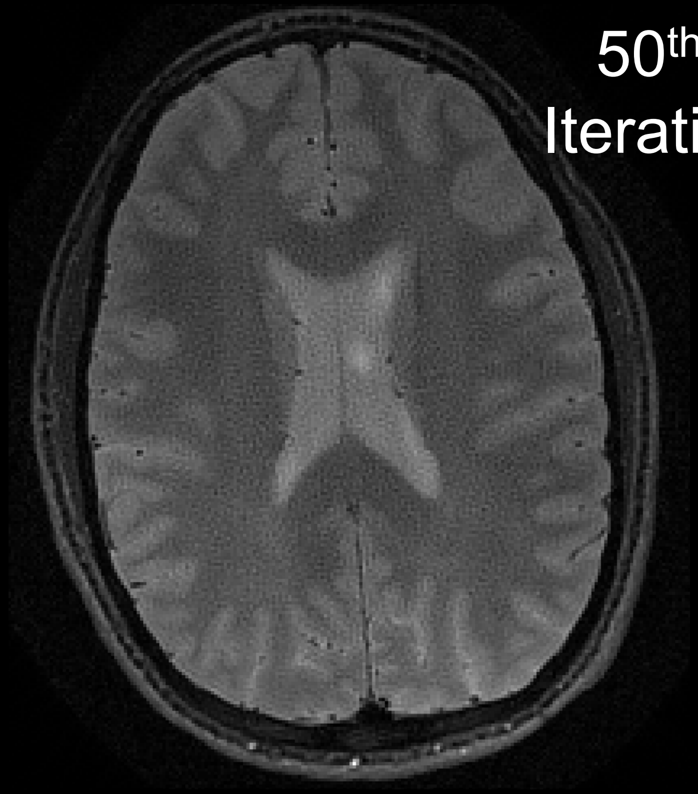


Images from: Hung Do, Canon Medical USA

How can the artifact be resolved?

A. Decrease the number of iterations
B. Increase the number of iterations
C. Remove regularization
D. Add noise pre-whitening step to the reconstruction pipeline



50th Iteration

CG-SENSE Recon in action!

Images from: Hung Do, Canon Medical USA

How can the artifact be resolved?

A. **Decrease the number of iterations**
B. Increase the number of iterations
C. Remove regularization
D. Add noise pre-whitening step to the reconstruction pipeline

CG-SENSE Recon in action!

7th Iteration

Images from: Hung Do, Canon Medical USA

Artifacts Explanation

Hung Do, PhD MSEE
Canon Medical Systems USA

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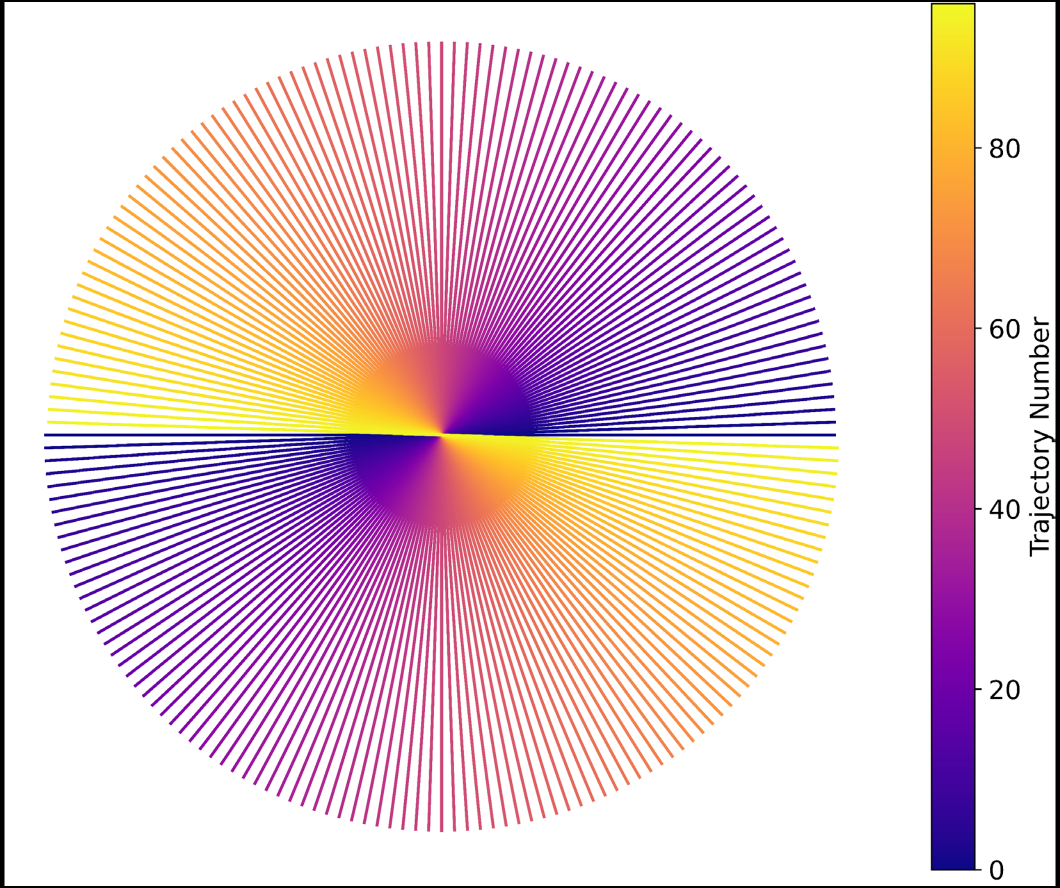
Radial k-space trajectory



Non-uniform k-space data:

- Denser low-frequency samples (center)
- Sparser high-frequency samples (periphery)

The non-uniformity must be compensated before reconstruction to avoid the *halo* artifact.

Gridding reconstruction

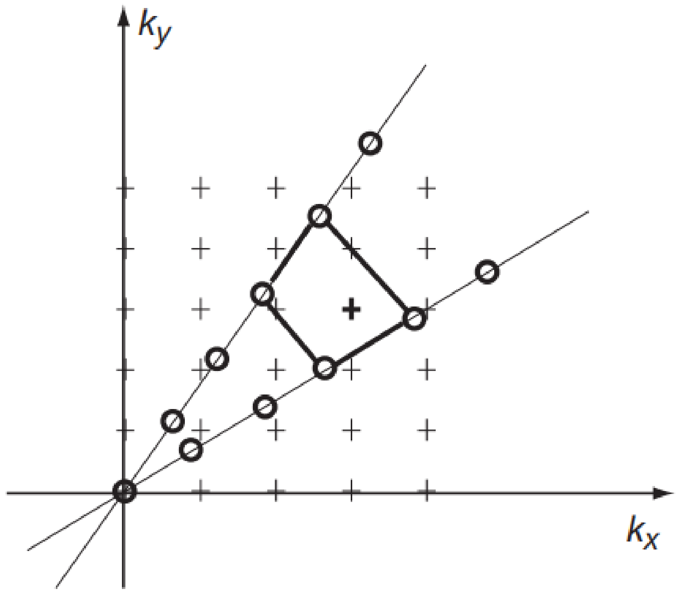


Figure 5.5: Grid-driven interpolation for a projection data set. Data samples lie on diameters in k-space. In this example the surrounding four data samples (o's) are located for each grid point (+'s), and a value at the grid point determined by bilinear interpolation.

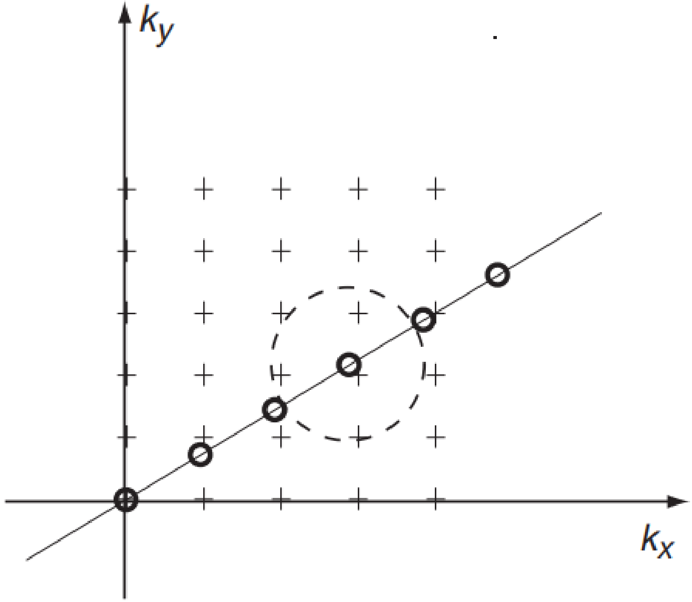


Figure 5.6: Data-driven interpolation for a projection data set. Again, data samples lie on diameters in k-space. Each data point is conceptually considered to be convolved with a small kernel, and the value of that convolution added to the adjacent k-space grid points.

Gridding reconstruction

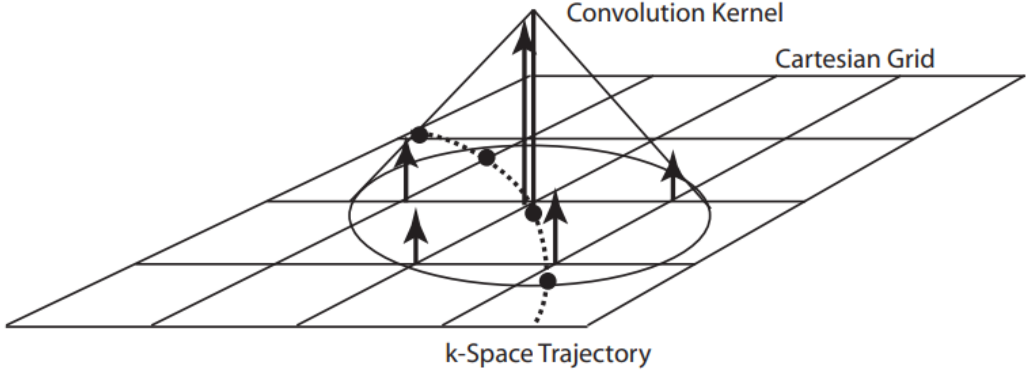
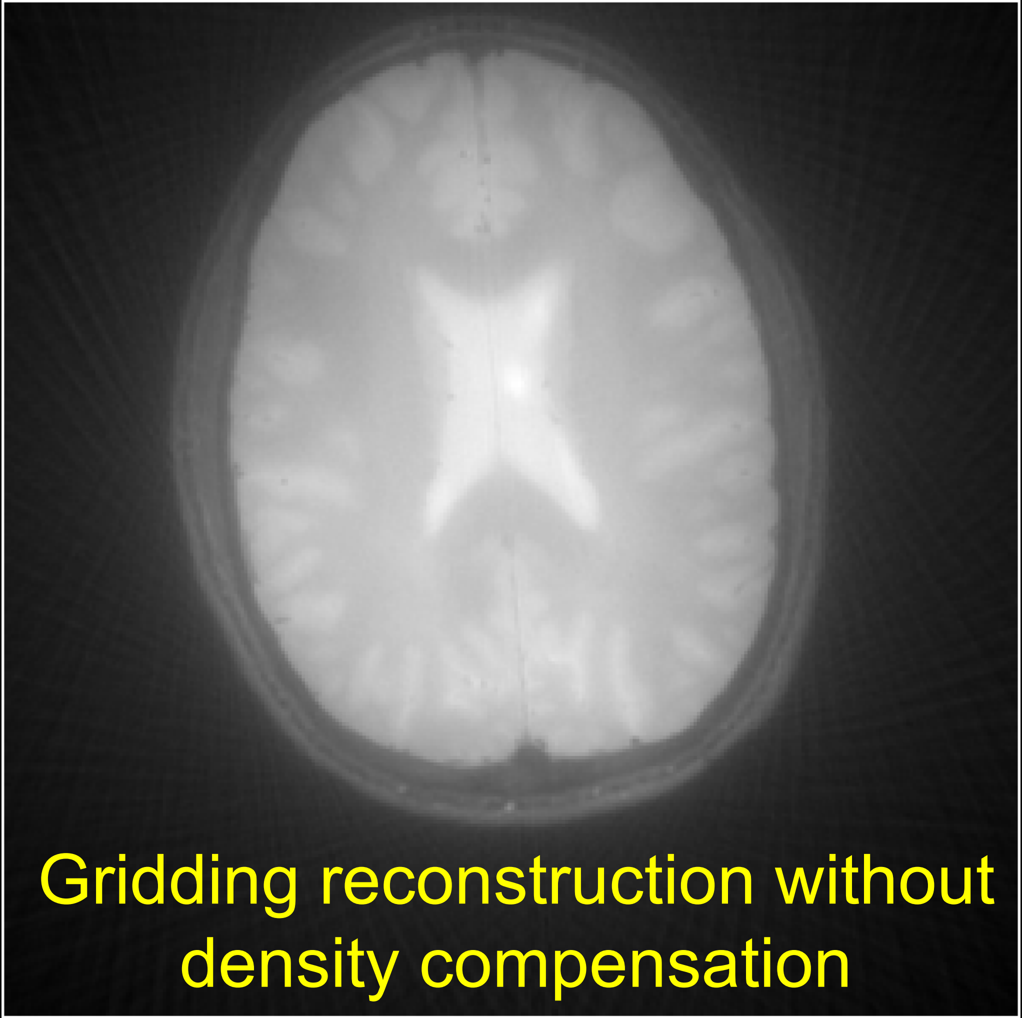
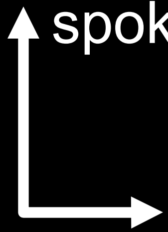


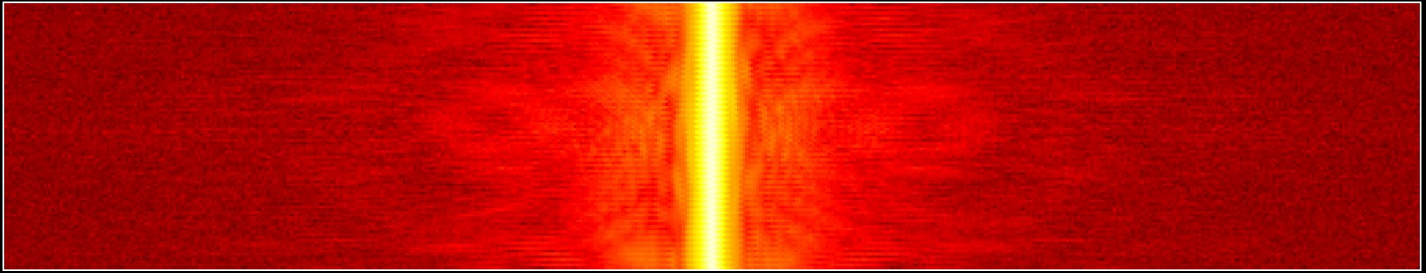
Figure 5.7: Basic gridding idea. The data samples line on some trajectory through k-space (dashed line). Each data point is conceptually convolved with a gridding kernel, and that convolution evaluated at the adjacent grid points.



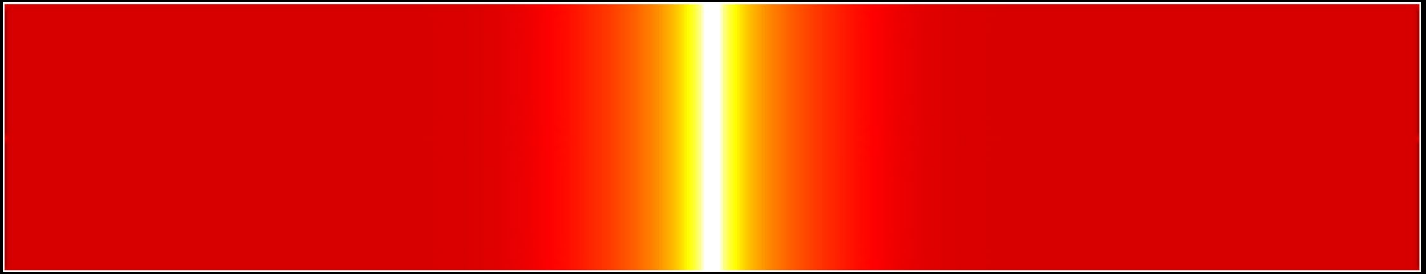
Gridding reconstruction without density compensation



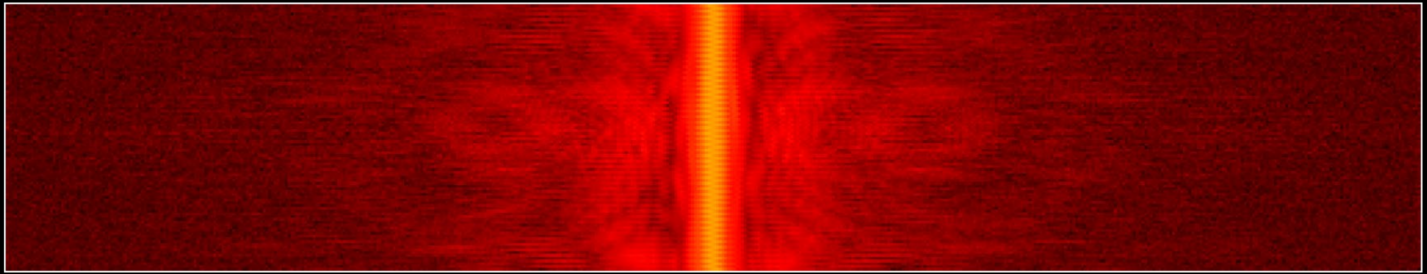
Raw k-space data ($\mathbf{m}$)



Density compensation function ($\mathbf{d_f}$)

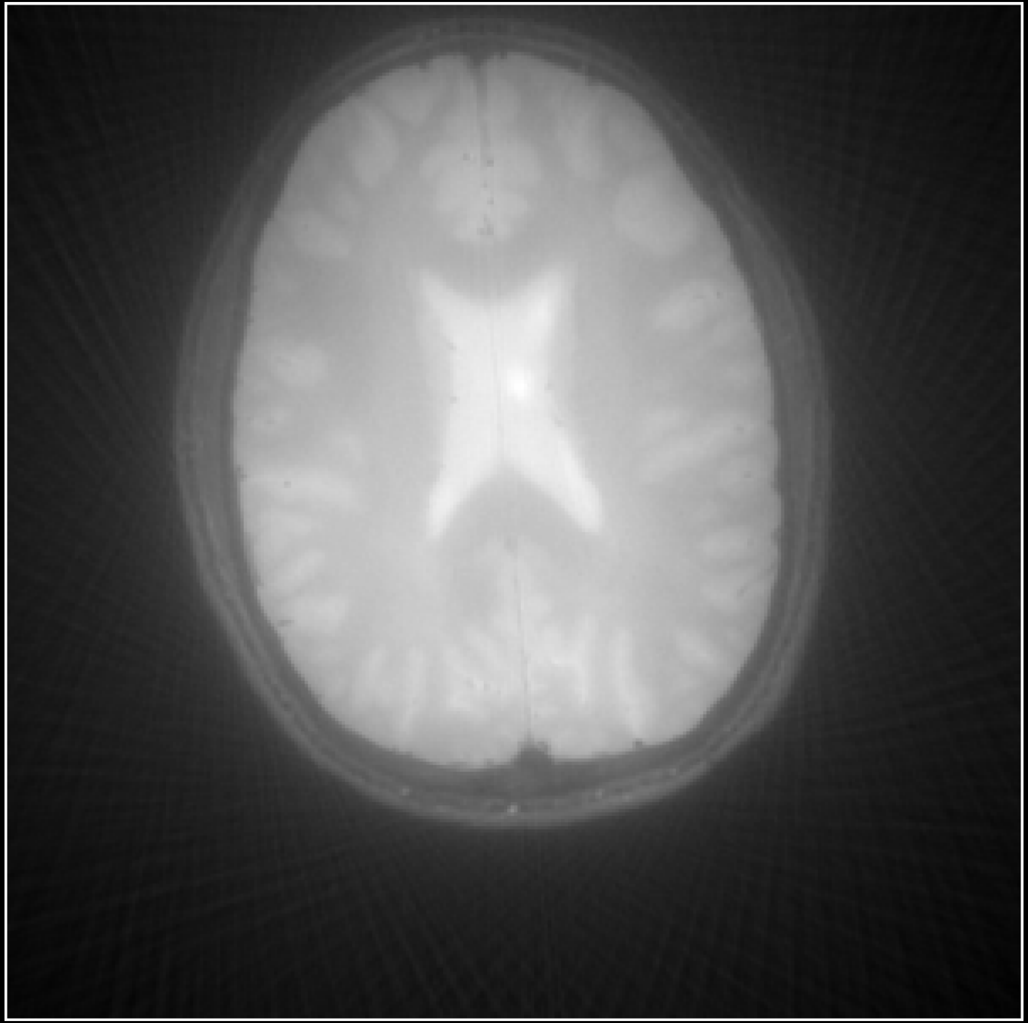


Density compensated data = $\mathbf{m/d_f}$

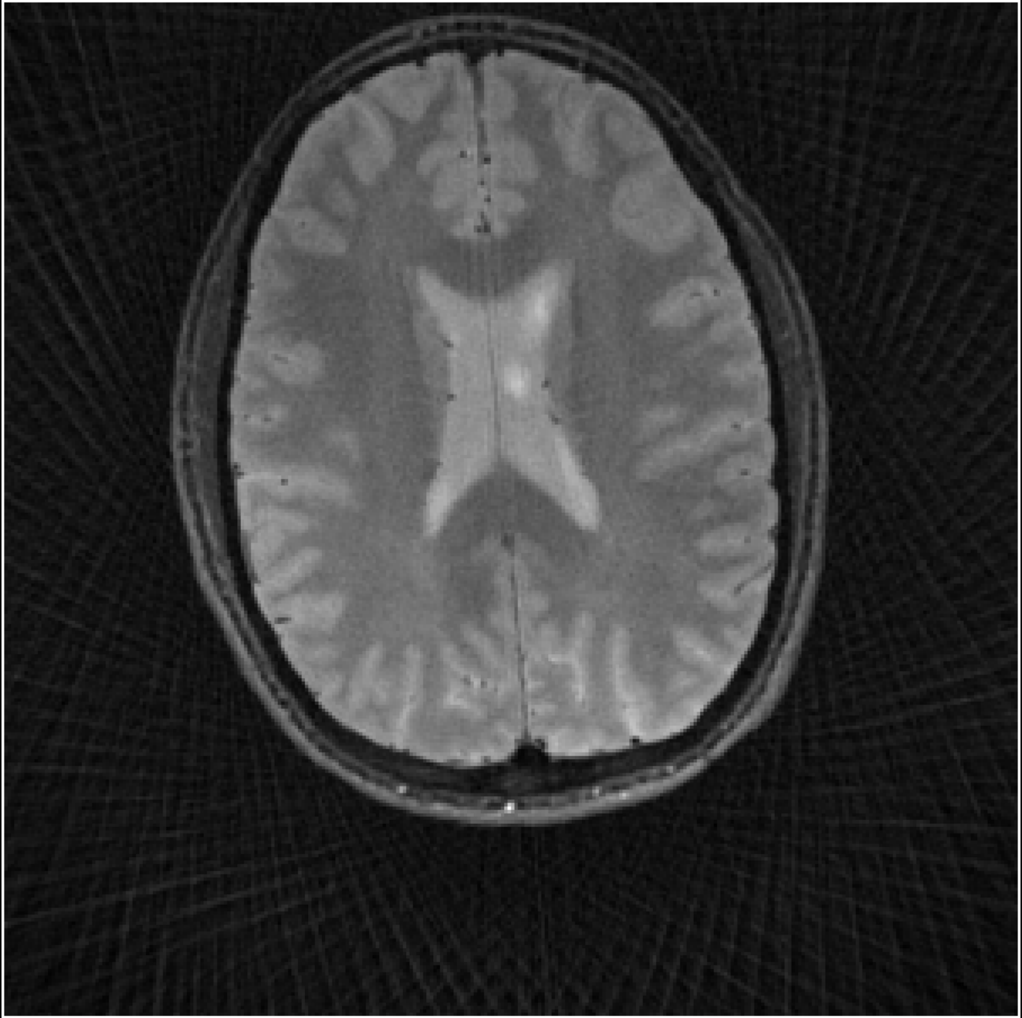


Density compensation step

Gridding reconstruction
without
density compensation

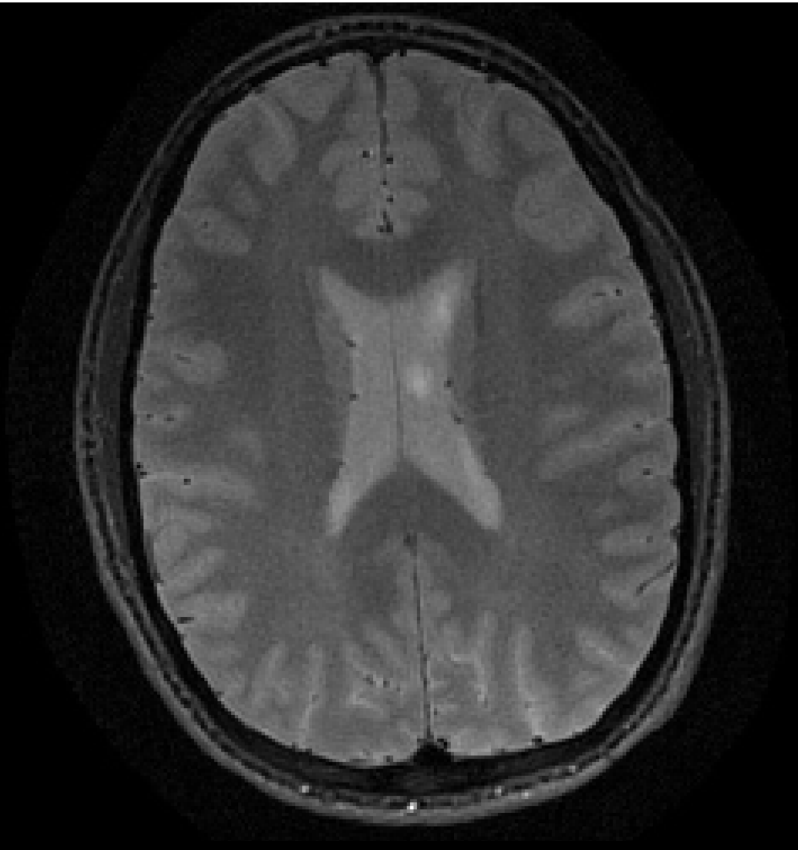


Gridding reconstruction
with
density compensation



SENSE and GRAPPA are for Cartesian k-space while CG-SENSE is for arbitrary k-space trajectories

CG-SENSE reduces streaking artifacts and improves image sharpness for radial MRI



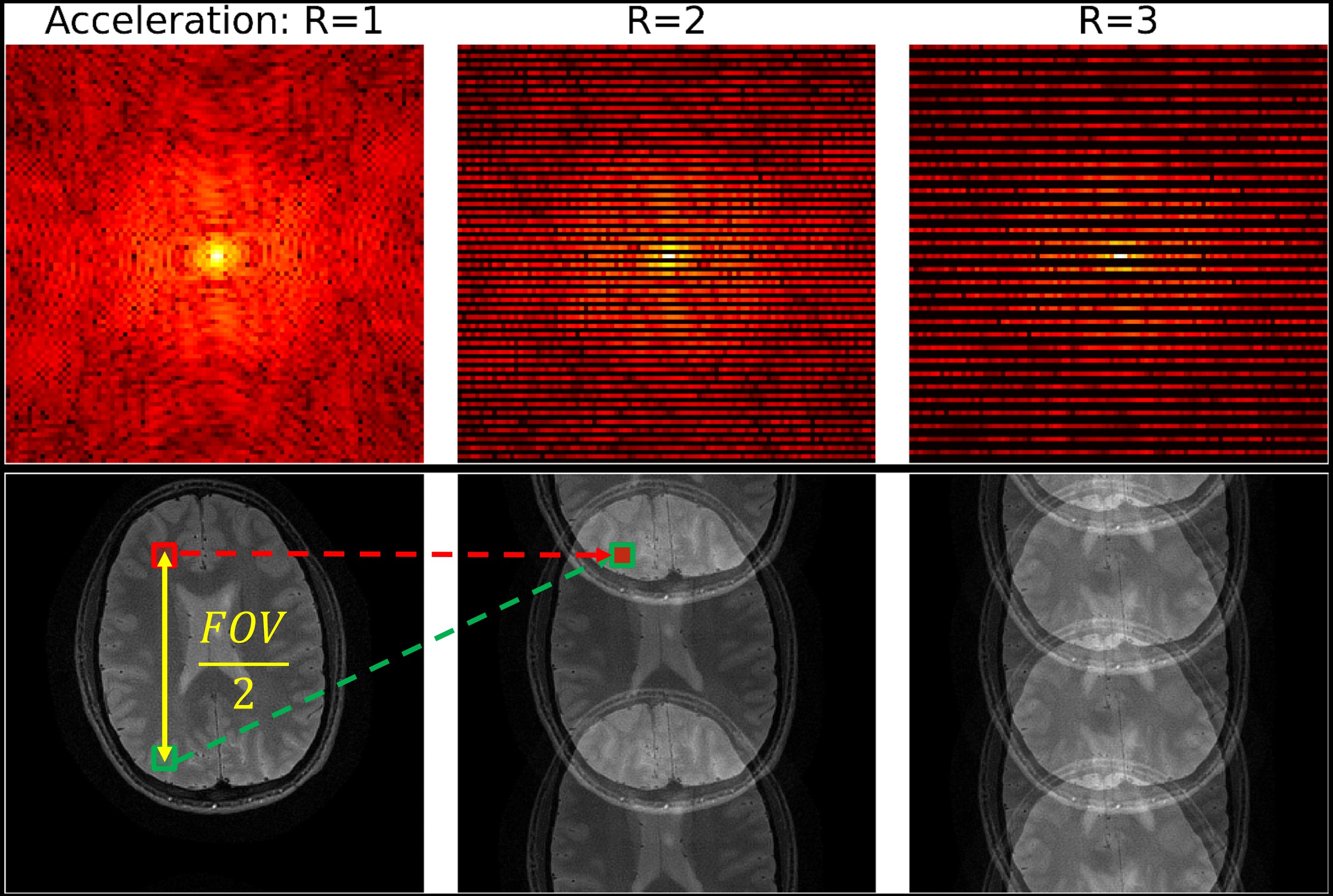
$$\hat{\mathbf{x}} = \mathbf{argmin}\, \|\mathbf{Ex} - \mathbf{m}\|_2^2$$

SENSE

Sensitivity Encoding: Parallel Imaging for Cartesian k-space

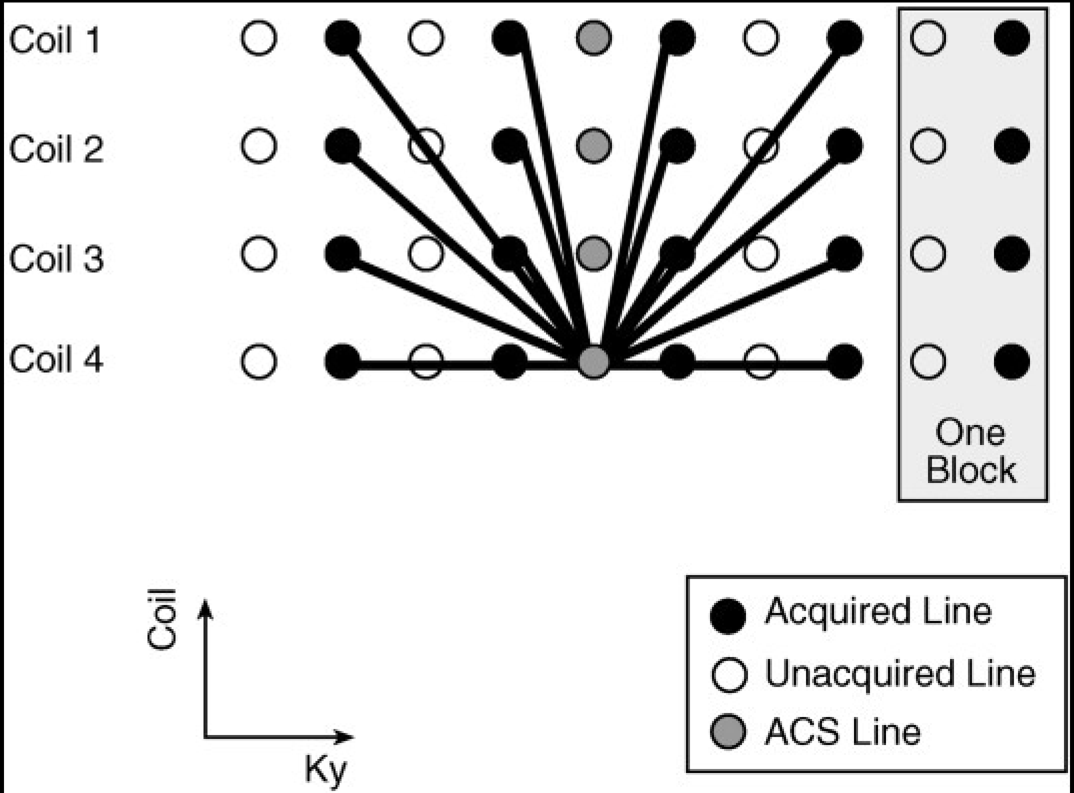
Cartesian k-space

FFT reconstruction



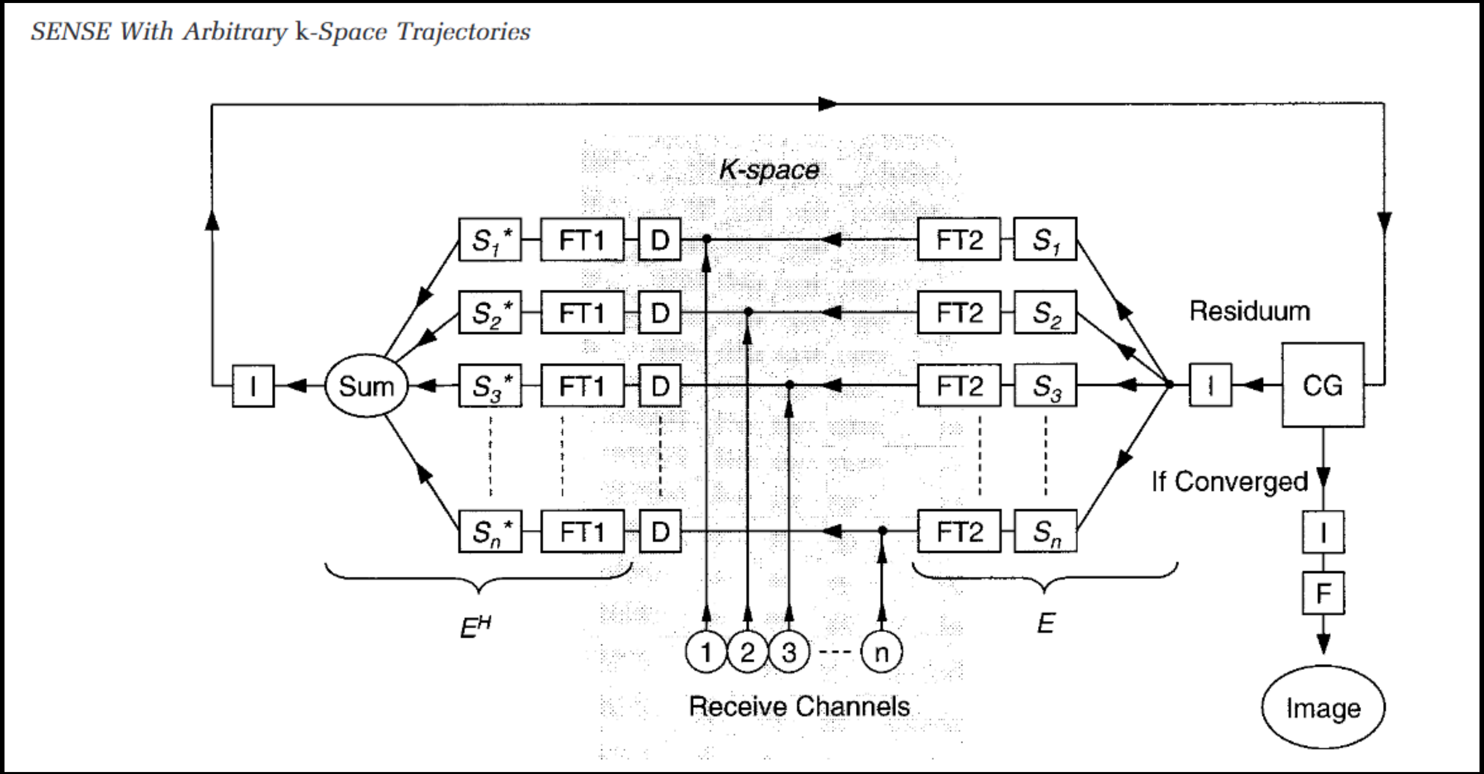
Pruessmann et al., Magn Reson Med. 1999;42:952-962.

Generalized autocalibrating partially parallel acquisitions (GRAPPA) for Cartesian k-space data



Griswold et al., Magnetic Resonance in Medicine 47.6 (2002): 1202-1210.

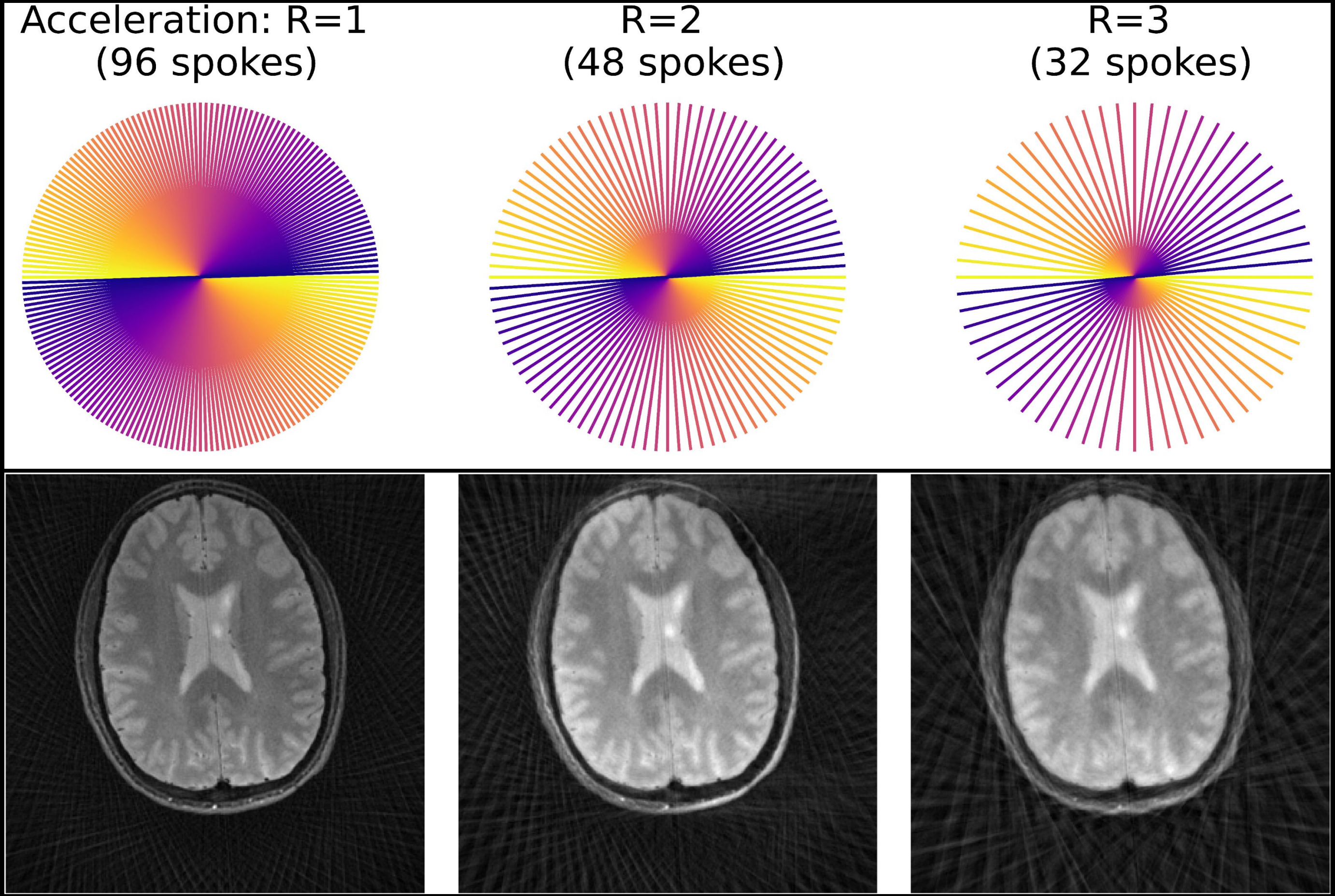
Conjugate Gradient SENSE reconstruction (CG-SENSE) for arbitrary k-space trajectories



Pruessmann et al., Magnetic Resonance in Medicine 46.4 (2001): 638-651.

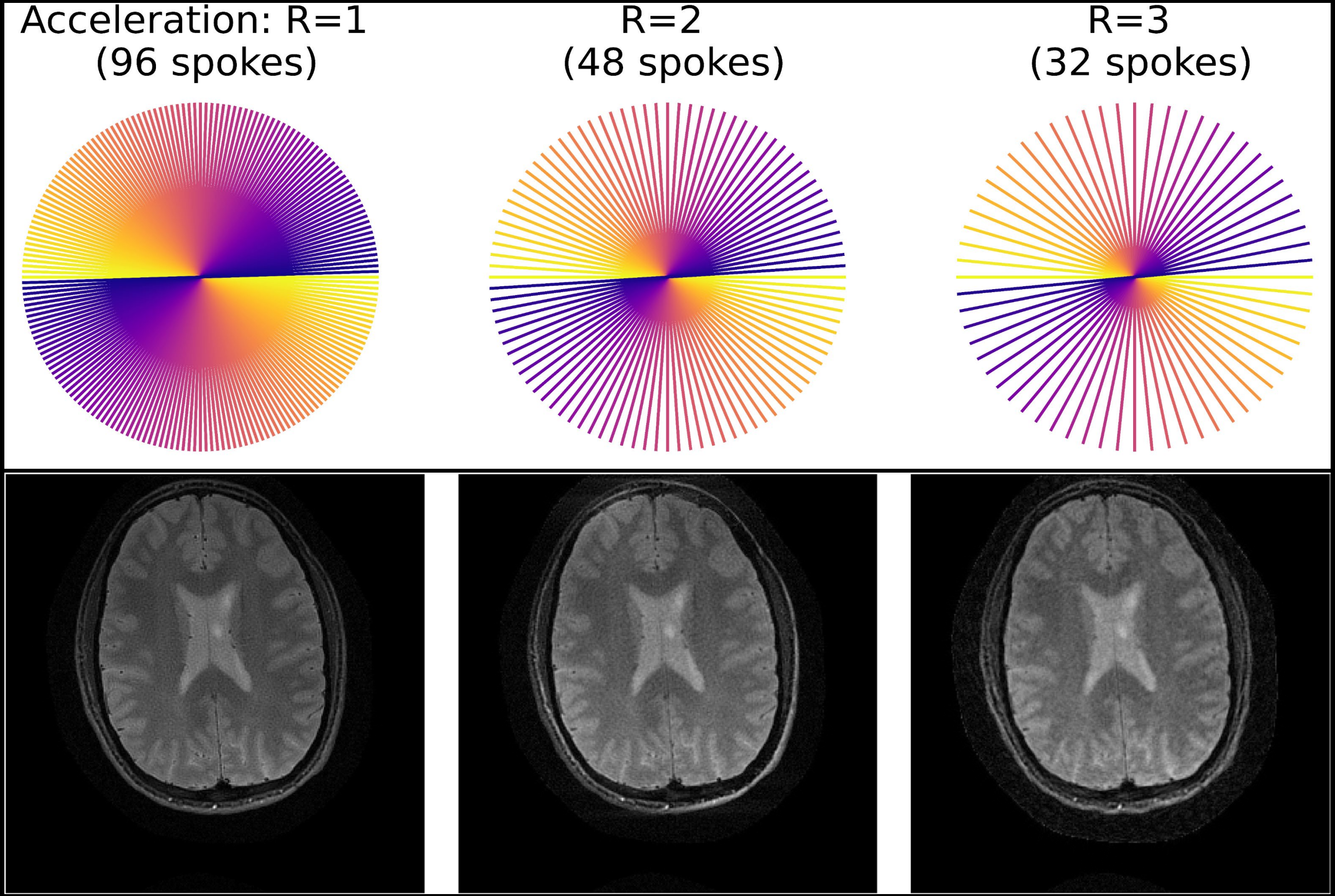
Radial
k-space
trajectory

Gridding
reconstruction



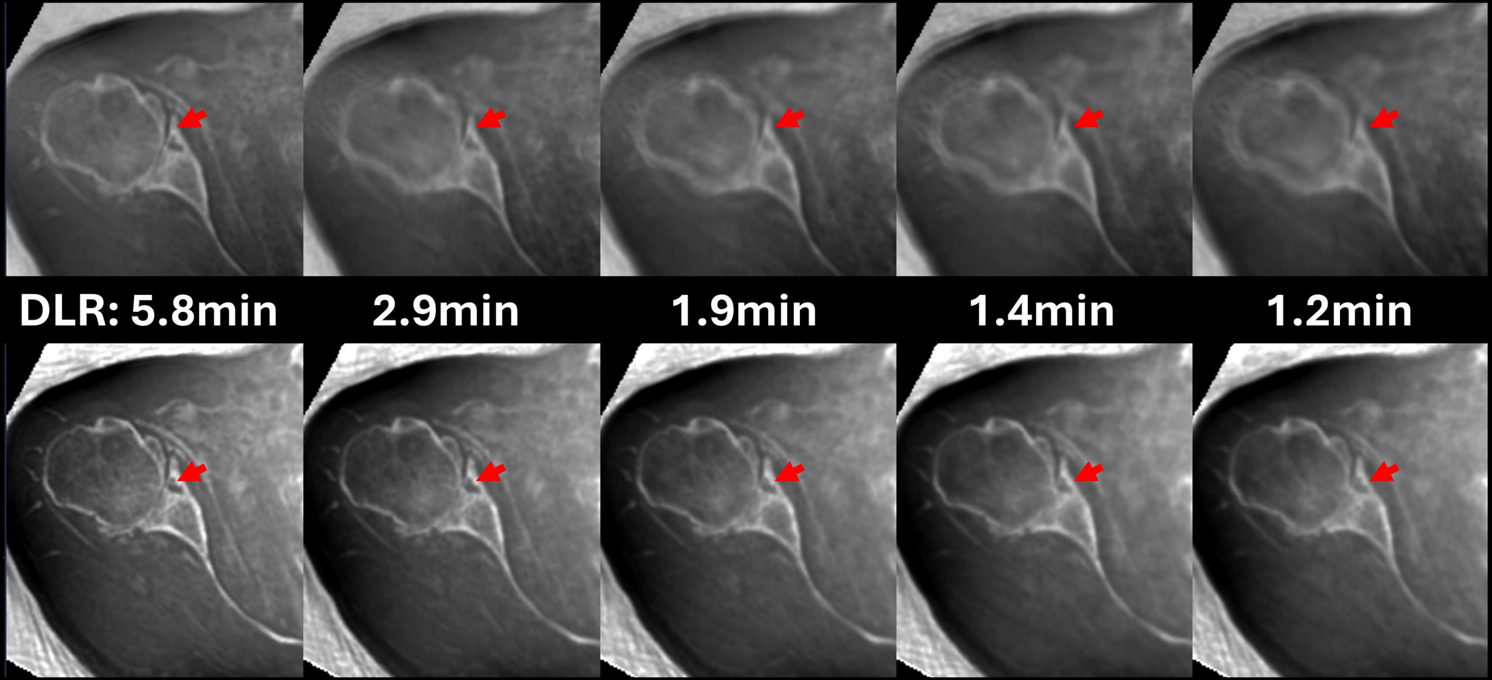
Radial
k-space
trajectory

CG-SENSE
reconstruction



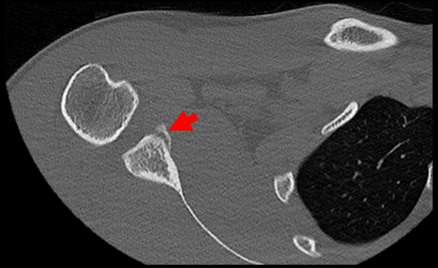
GRID: 5.8min 2.9min 1.9min 1.4min 1.2min

DLR: 5.8min 2.9min 1.9min 1.4min 1.2min



Bony Bankart Lesion (arrow)

CT



Hung Do *et al.*, ISMRM 2025, Abstract #0156

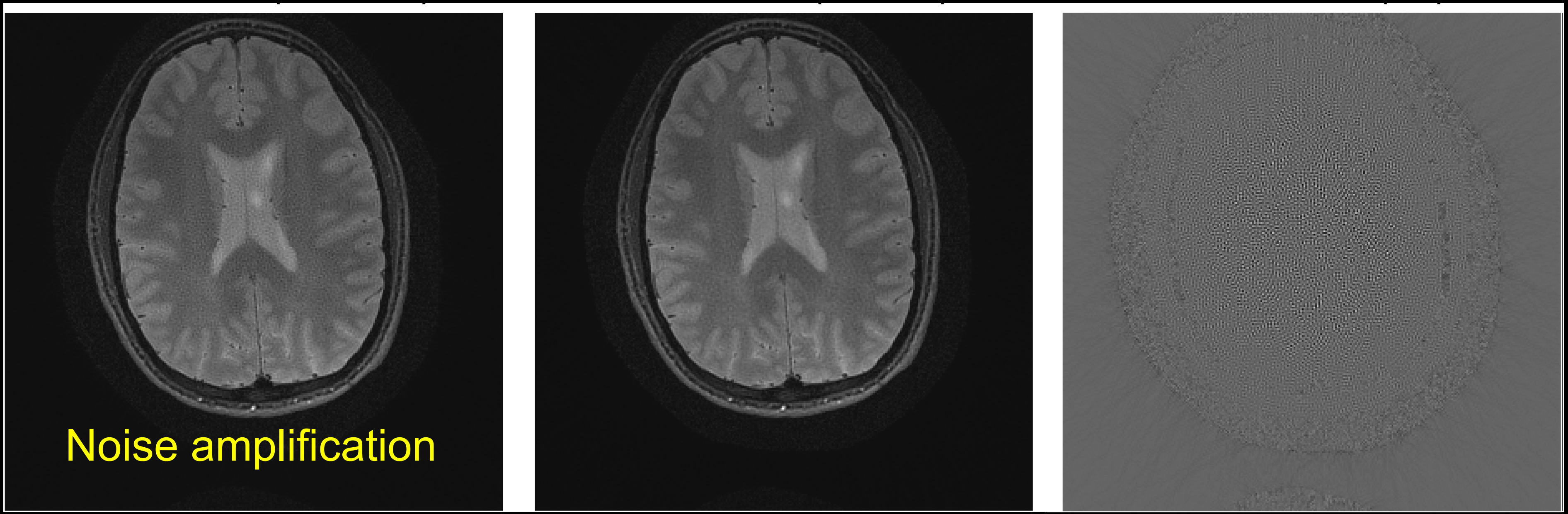
4-echo UTE, 0.8mm^3 3D isotropic with CG-SENSE & Deep Learning Denoising Recon (DLR) vs. Gridding

Bonus: Challenging Artifact

The Semi-convergence Behavior of CG-SENSE

Noise amplification with a high number of iterations

50th iteration | 7th iteration | difference (10x)

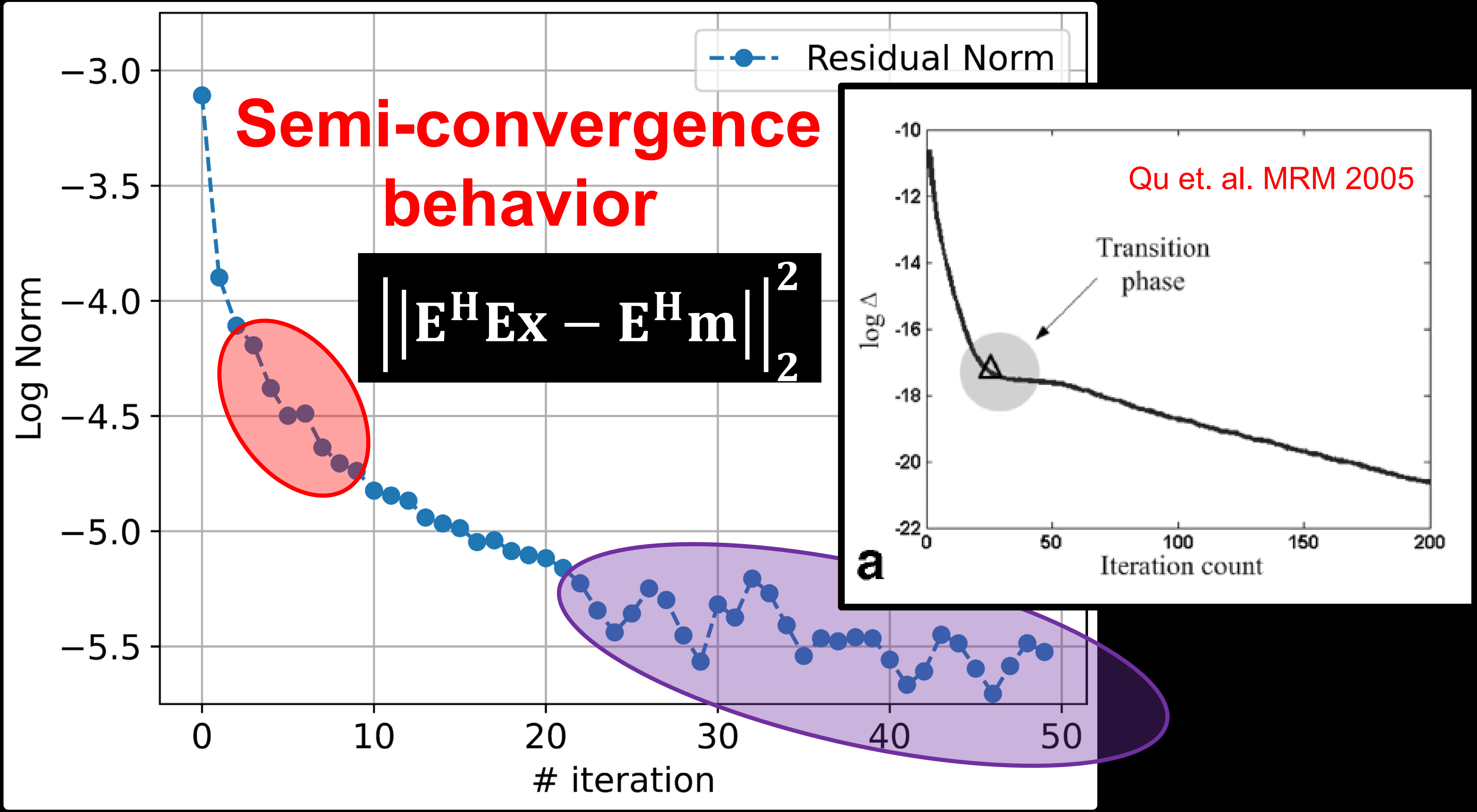


CG-SENSE's Semi-convergence

- *"Semi-convergence is characterized by initial convergence toward the optimal solution but later divergence"* (Qu *et al*., MRM 2005).
- The under-sampled k-space data causes the inverse problem ill-posed, which in turns leads to the semi-convergence behavior.
- The semi-convergence is not unique to MRI, it is a feature of the Conjugate Gradient or Gradient Descent algorithm when a problem is ill-posed.

Troubleshooting

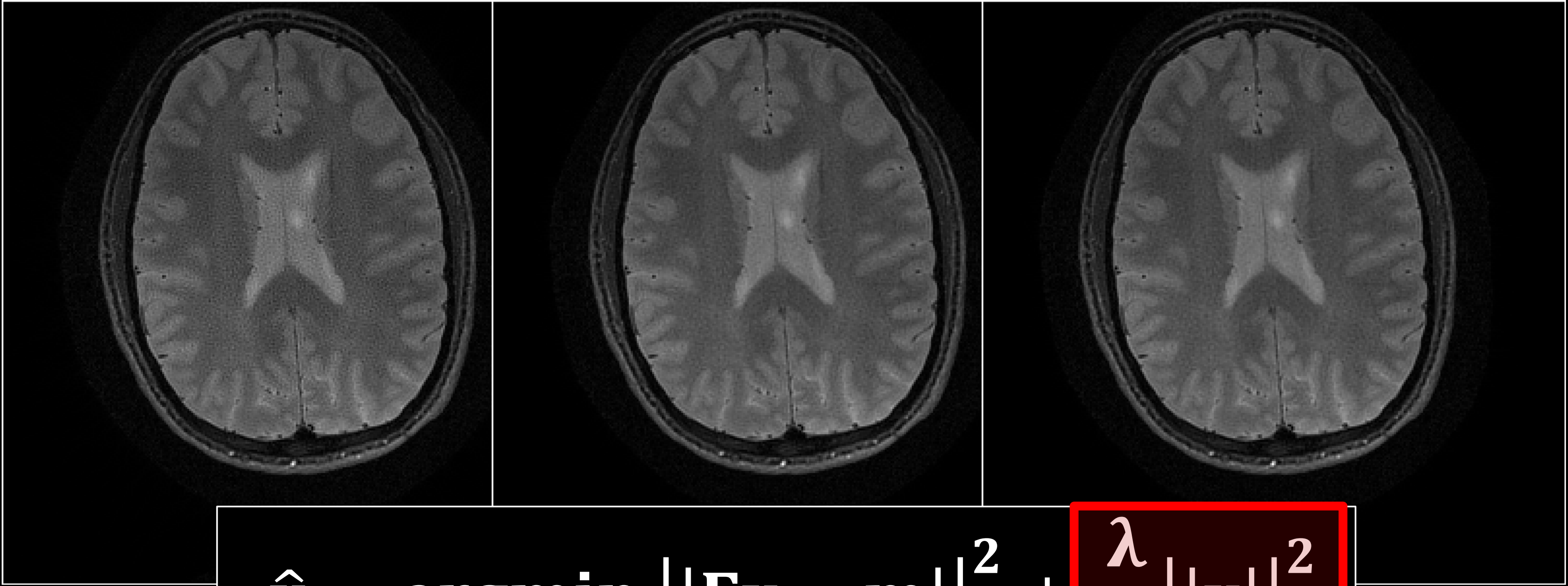
1. My first response, when I saw the grainy (noise-like) artifacts, was to increase the number of iterations, hoping that the reconstructed image would come closer toward the optimal solution (un-aware of the *semi-convergence* behavior). However, the noise amplification got worse.
2. Second, I wondered if there is a bug in the CG implementation. I decided to reimplement different variants of the CG algorithm, but the artifacts remained.
3. Third, I implemented gradient descent algorithm, but the artifacts persisted.
4. Fourth, I inspected the intermediate images and plotted residual norm vs. number of iterations. Residual norm behaved funny at high iteration count, but I wasn't sure why.
5. Finally, I found the Qu *et al.*, MRM2005 and learned about the *semi-convergence* phenomenon.
6. The solution is to use early stopping or to implement CG with regularizations.


Semi-convergence
behavior
$\left\|E^H E x - E^H m\right\|_2^2$
Residual Norm
Log Norm
iteration
−3.0
−3.5
−4.0
−4.5
−5.0
−5.5
0
10
20
30
40
50
Qu et. al. MRM 2005
Transition
phase
log Δ
Iteration count
-10
-12
-14
-16
-18
-20
-22
0
50
100
150
200
a

Noise amplification

Tikhonov regularization

Early stopping



$$\hat{\mathbf{x}} = \mathbf{argmin} \, ||\mathbf{Ex} - \mathbf{m}||_2^2 + \boxed{\frac{\boldsymbol{\lambda}}{2}||\mathbf{x}||_2^2}$$

Other Regularizations

Early stopping and Tikhonov regularization mitigate the noise amplification, other advanced regularizations also work:

- L1-regularization in the sparsifying transform domain as in Compressed Sensing reconstruction,
- Data-driven regularization as in Deep Neural Network-based reconstruction, etc.

$$\hat{\mathbf{x}} = \mathbf{argmin}\,||\mathbf{Ex} - \mathbf{m}||_2^2 + \mathbf{R(x)}$$

m: measured k-space

E: encoding matrix

x: intermediate reconstructed image

R(x): regularization function

References

1. Qu, Peng, et al. "Convergence behavior of iterative SENSE reconstruction with non-Cartesian trajectories.“Magnetic Resonance in Medicine 54.4 (2005): 1040-1045.
2. Pruessmann, Klaas P., et al. "Advances in sensitivity encoding with arbitrary k-space trajectories.“ Magnetic Resonance in Medicine 46.4 (2001): 638-651.
3. Maier, Oliver, et al. "CG-SENSE revisited: Results from the first ISMRM reproducibility challenge." Magnetic Resonance in Medicine 85.4 (2021): 1821-1839.
4. Griswold, Mark A., et al. "Generalized autocalibrating partially parallel acquisitions (GRAPPA)." Magnetic Resonance in Medicine 47.6 (2002): 1202-1210.
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7. Professor John Pauly’s Lecture on “Reconstruction of Non-Cartesian Data”, Stanford University
8. Pruessmann, Klaas P., et al. "SENSE: sensitivity encoding for fast MRI." Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine 42.5 (1999): 952-962.