FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG

TECHNISCHE FAKULTÄT

Deep Learning Image Reconstruction in MRI

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Department Artificial Intelligence in Biomedical Engineering (AIBE)

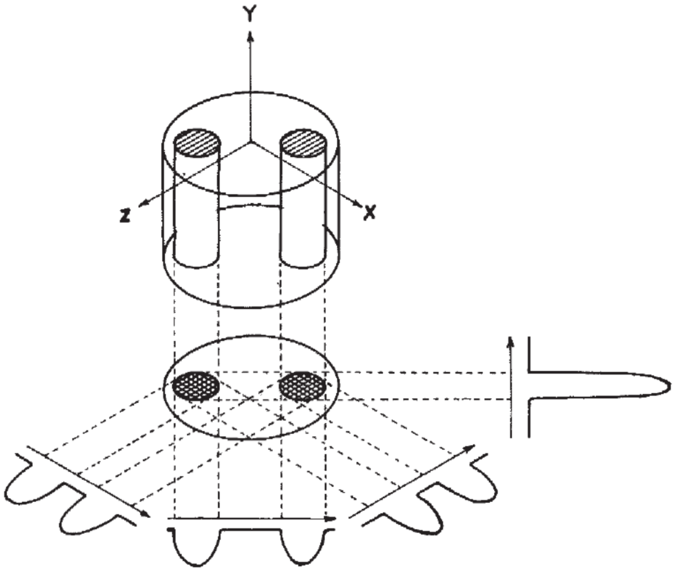
June 28, 2022

Outline

1 Magnetic Resonance Imaging

Magnetic Resonance Imaging (MRI)

✓ Lauterbur PC. Image formation by induced local interactions: Examples employing nuclear magnetic resonance. *Nature* (1977).



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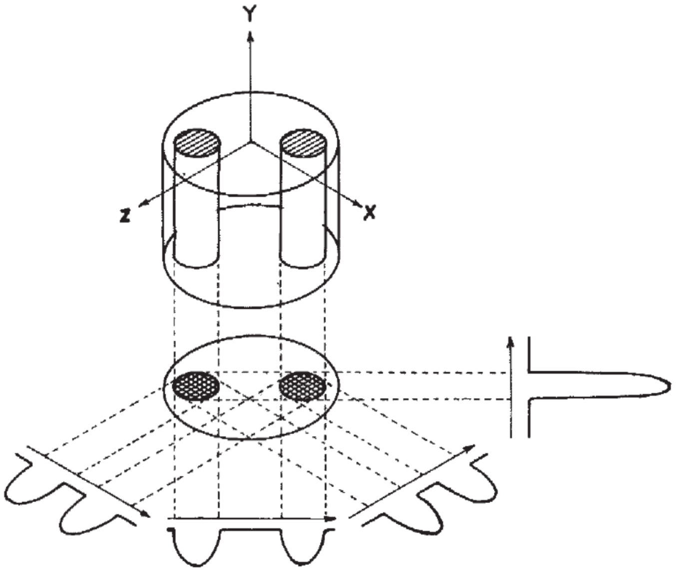
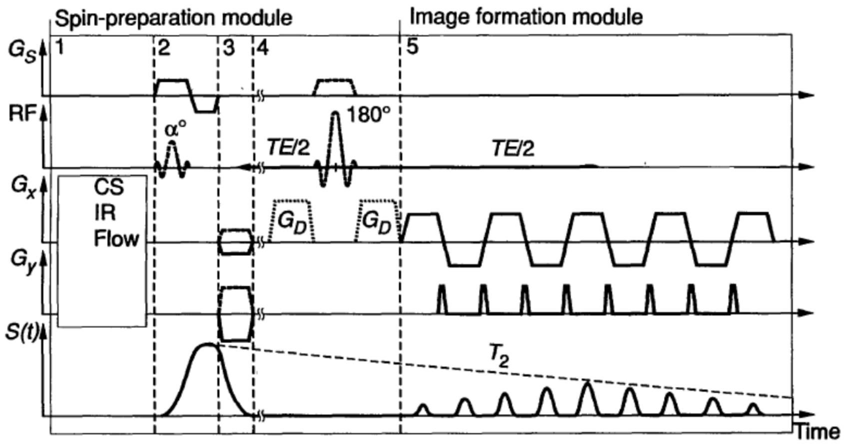


- ✓ Mansfield P. Multi-planar imaging formation using NMR spin echoes. *J Phys C* (1977).
- ✓ Stehling MK, Turner R, Mansfield P. Echo-planar imaging: MRI in a fraction of a second. *Science* (1991).



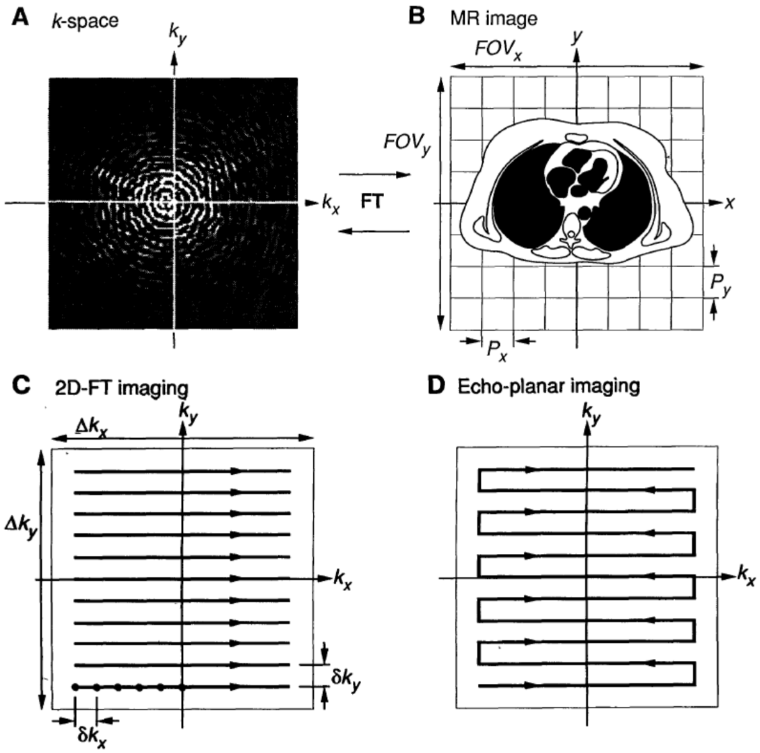
MRI is a Fourier Machine [1]

A. MRI acquires data in Fourier domain (k-space).

B. MR Image can be reconstructed via Fast Fourier Transform (FFT).

C. 2D-FT imaging requires one excitation per k-space line.

D. In EPI, k-space is sampled in a single, continuous trajectory within a fraction of a second.



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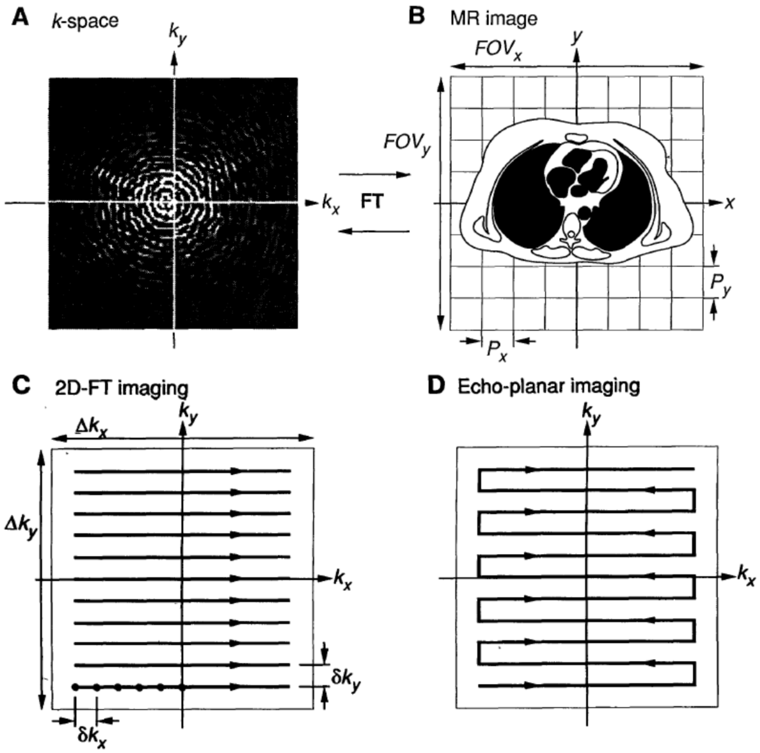
X Trade-off between spatial/temporal resolution and SNR.



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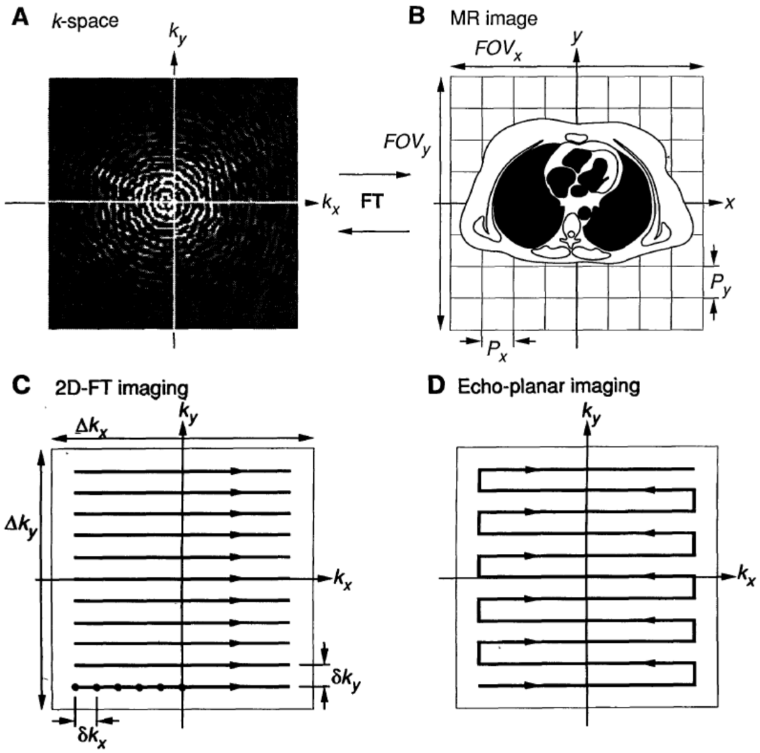
X Trade-off between spatial/temporal resolution and SNR.

X Point-wise sampling of k-space requires long scan time.



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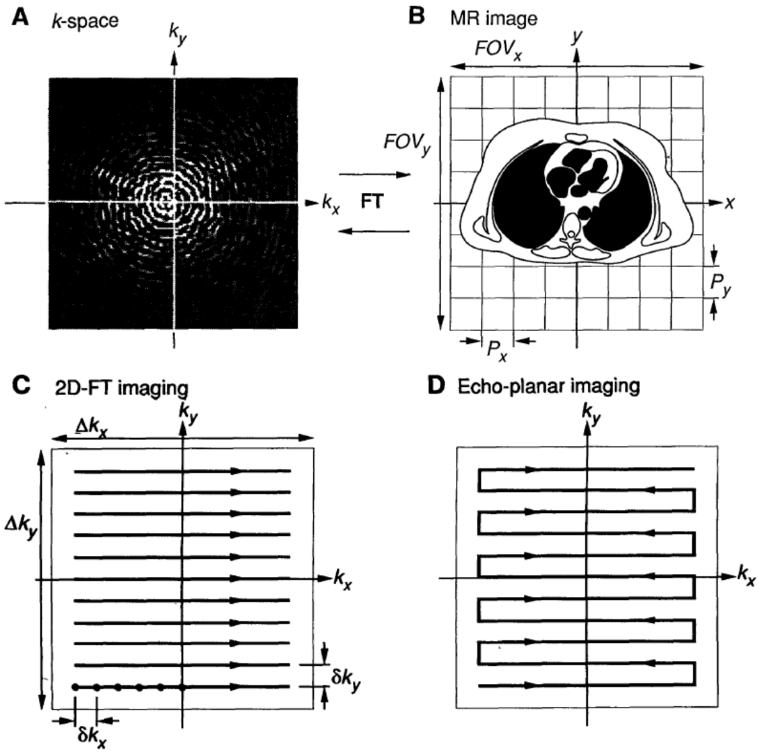
X Perturbed k-space data, e.g. subject motion, trajectory imperfection, field inhomogeneity ...



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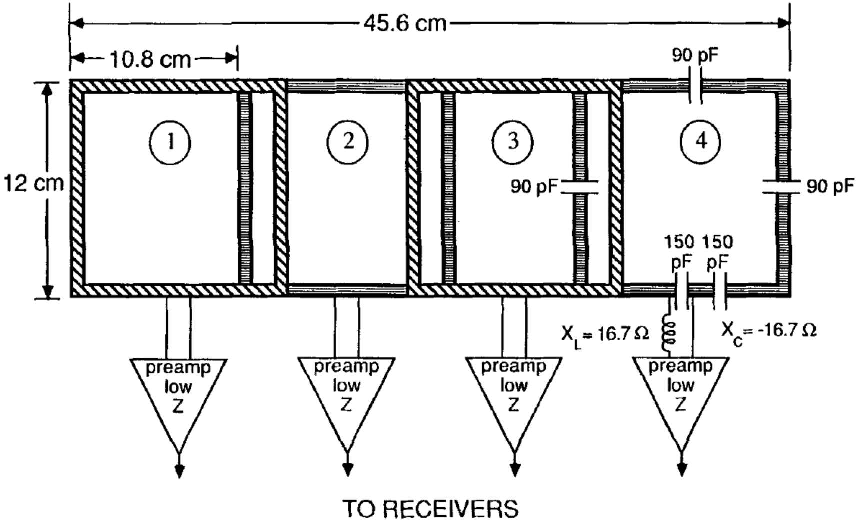
2 Image Reconstruction in MRI

Outline

Parallel Imaging: Multiple Receiver Coils [2]

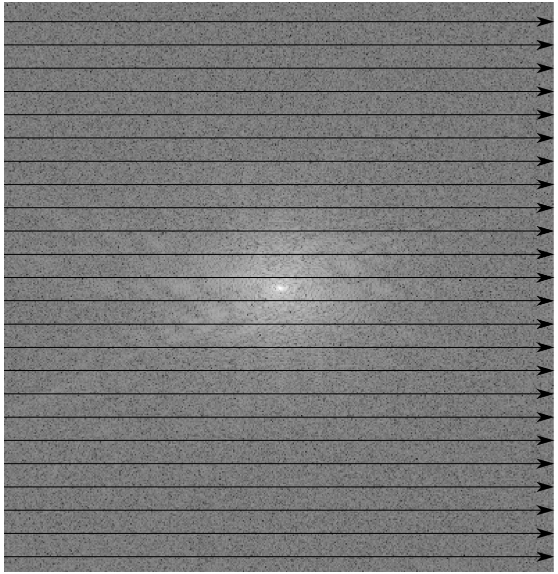
✓ Boost SNR with no increase in scan time.

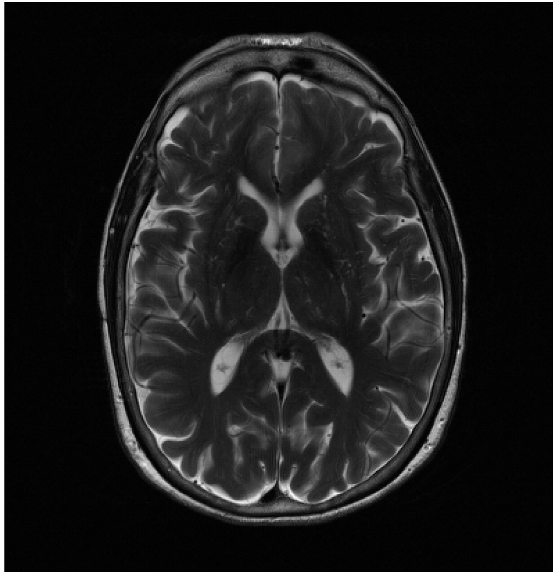


[2] Roemer PB, et al. The NMR phase array. *Magn Reson Med* (1990).

Parallel Imaging in Combination with k-Space Undersampling

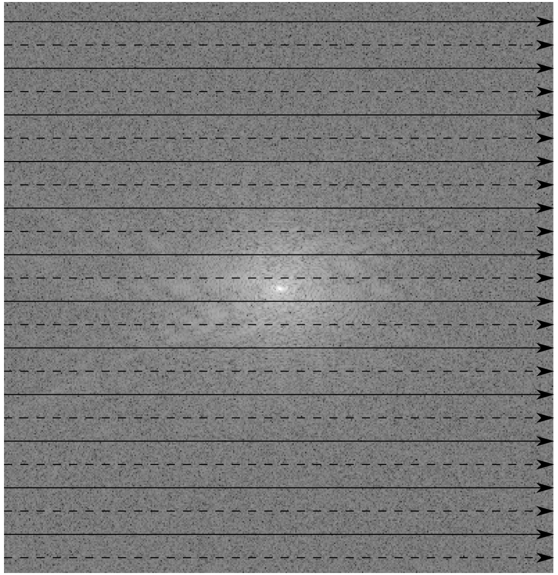
- Data source: `https://fastmri.org/`.
- Image reconstruction via inverse FFT and root sum square over coils.

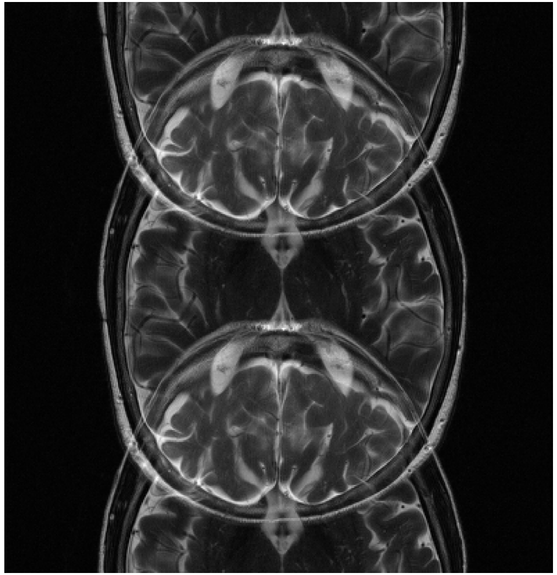




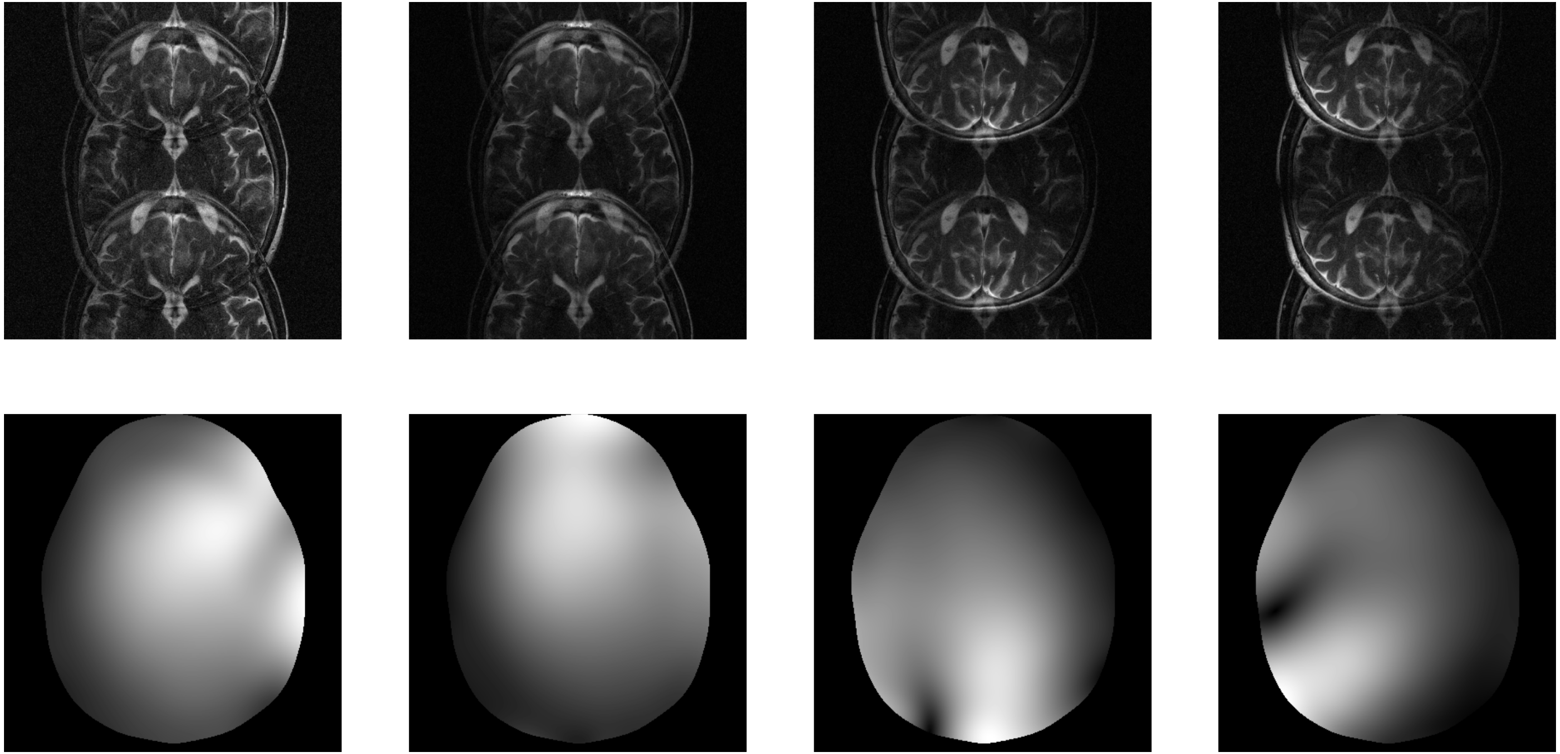
Parallel Imaging in Combination with k-Space Undersampling

- Data source: `https://fastmri.org/`.
- k-space undersampling causes artifacts. In this case, acceleration factor $R = 2$.



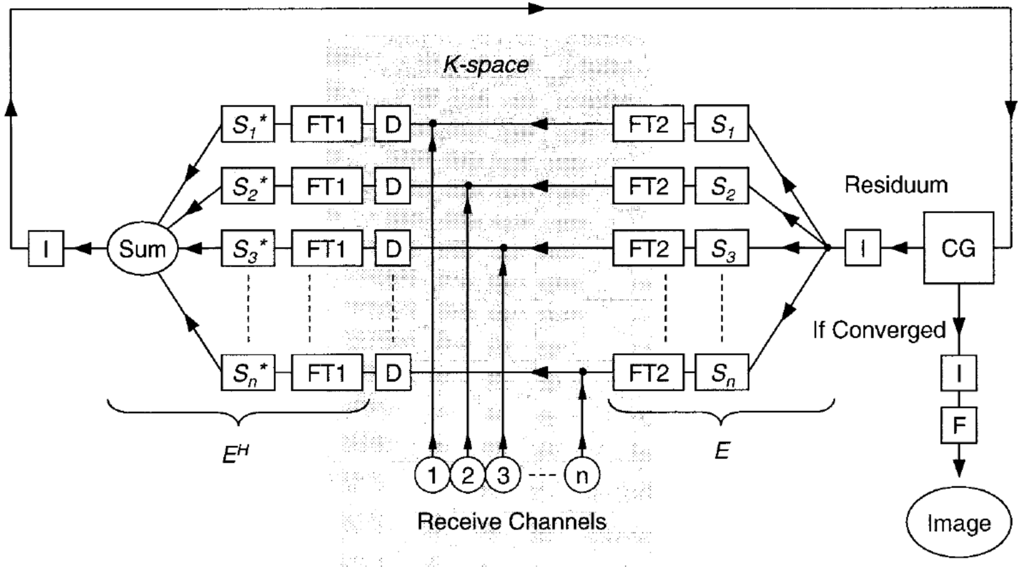


Multiple Coil Images & Calibrated Coil Sensitivity Maps [3]



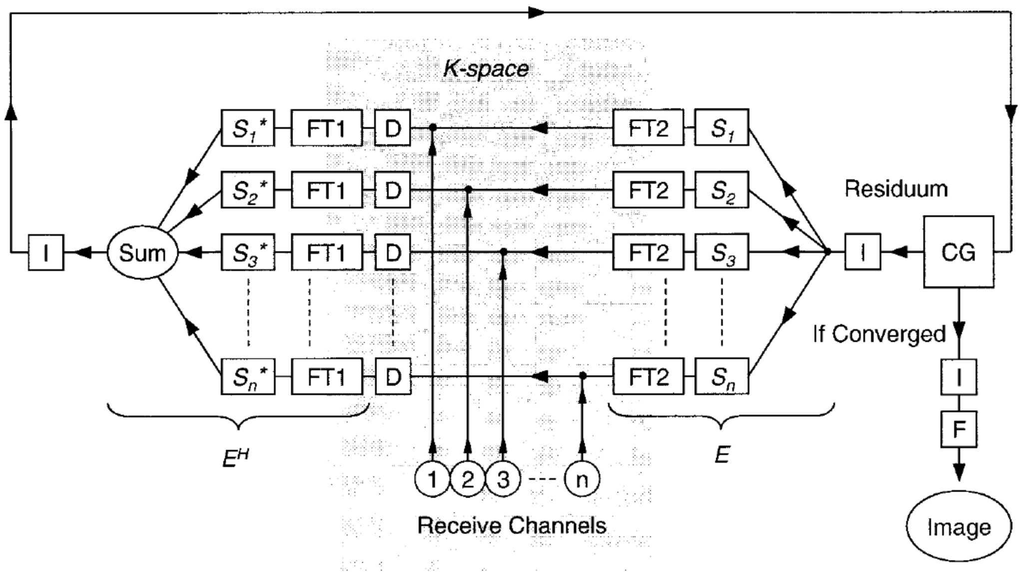
[3] Uecker M, et al. ESPIRiT – An eigenvalue approach to autocalibrating parallel MRI: Where SENSE meets GRAPPA. *Magn Reson Med* (2014).

Parallel Imaging Reconstruction: SENSE [4, 5]



[4] Pruessmann KP, et al. SENSE: Sensitivity encoding for fast MRI. *Magn Reson Med* (1999).
[5] Pruessmann KP, et al. Advances in sensitivity encoding with arbitrary k-space trajectories. *Magn Reson Med* (2001).

Parallel Imaging Reconstruction: SENSE [4, 5]



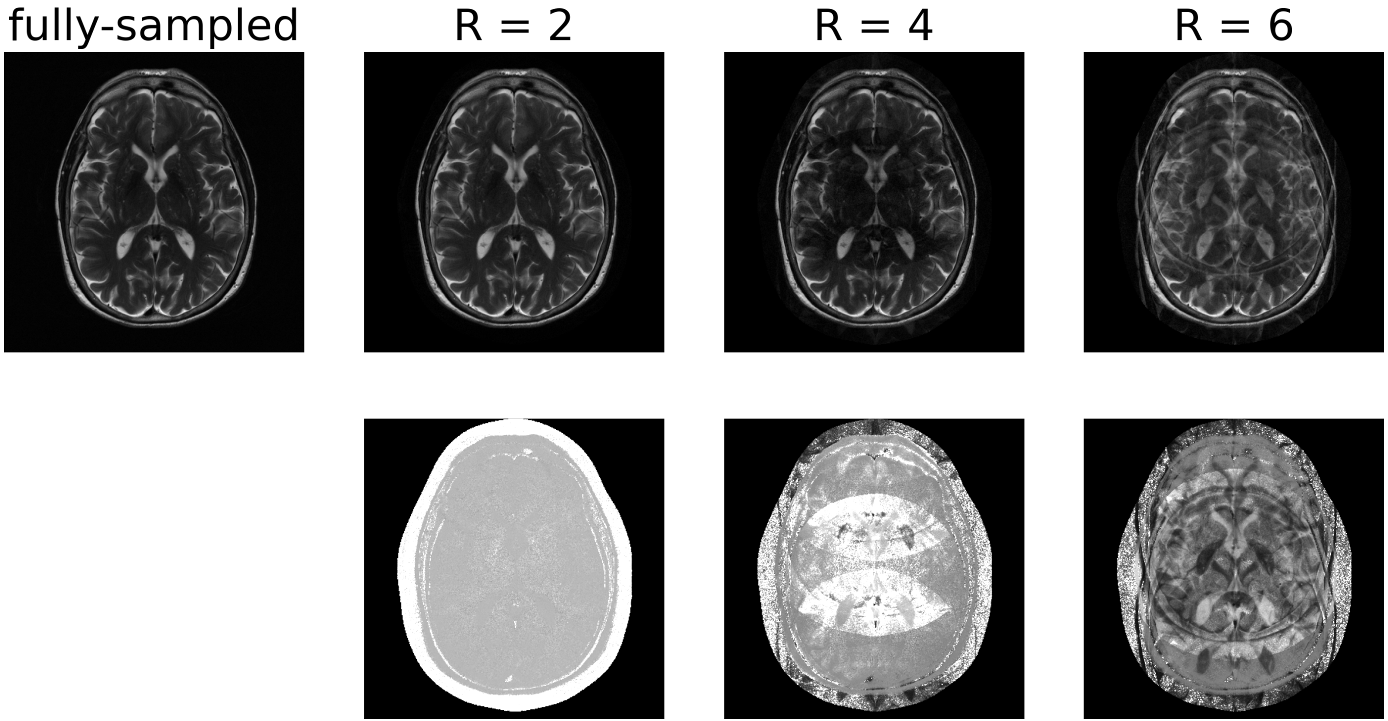
- System of linear equations:

$$\begin{cases} \mathcal{F}_u\{c_1 \cdot \rho\} = y_1 \\ \mathcal{F}_u\{c_2 \cdot \rho\} = y_2 \\ \vdots \\ \mathcal{F}_u\{c_N \cdot \rho\} = y_N \end{cases} \tag{1}$$

- Solved via conjugate gradient method.

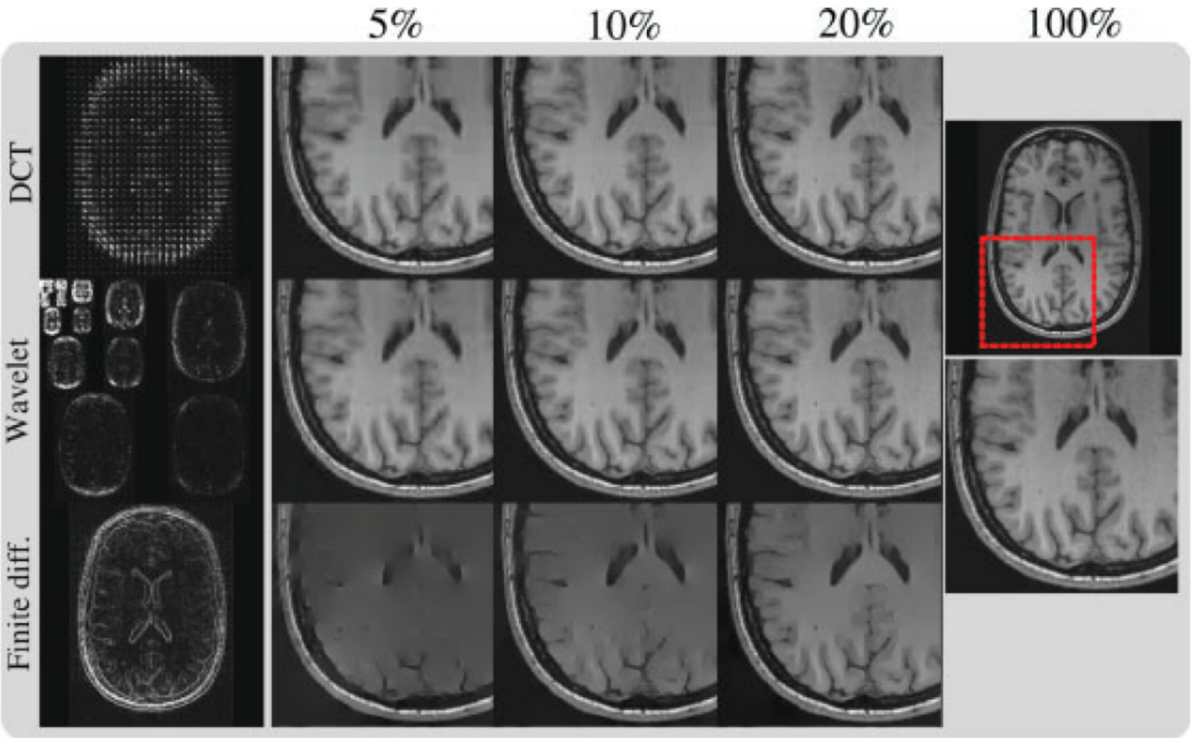
[4] Pruessmann KP, et al. SENSE: Sensitivity encoding for fast MRI. *Magn Reson Med* (1999).
[5] Pruessmann KP, et al. Advances in sensitivity encoding with arbitrary k-space trajectories. *Magn Reson Med* (2001).

Parallel Imaging Reconstruction: SENSE



Outline

Compressed Sensing [6, 7]



[6] Candès EJ, et al. Stable signal recovery from incomplete and inaccurate measurements. *Commun Pure Appl Math* (2006).
[7] Lustig M, et al. Sparse MRI: The application of compressed sensing for rapid MRI. *Magn Reson Med* (2007).

Parallel Imaging Compressed Sensing (PICS) Reconstruction [8, 9]

- SENSE solves a linear inverse problem:

$$\Phi(x) = \mathrm{argmin}_x \left\| \mathcal{F}_u S x - y \right\|_2^2 + \alpha \left\| x \right\|_2^2 \tag{2}$$

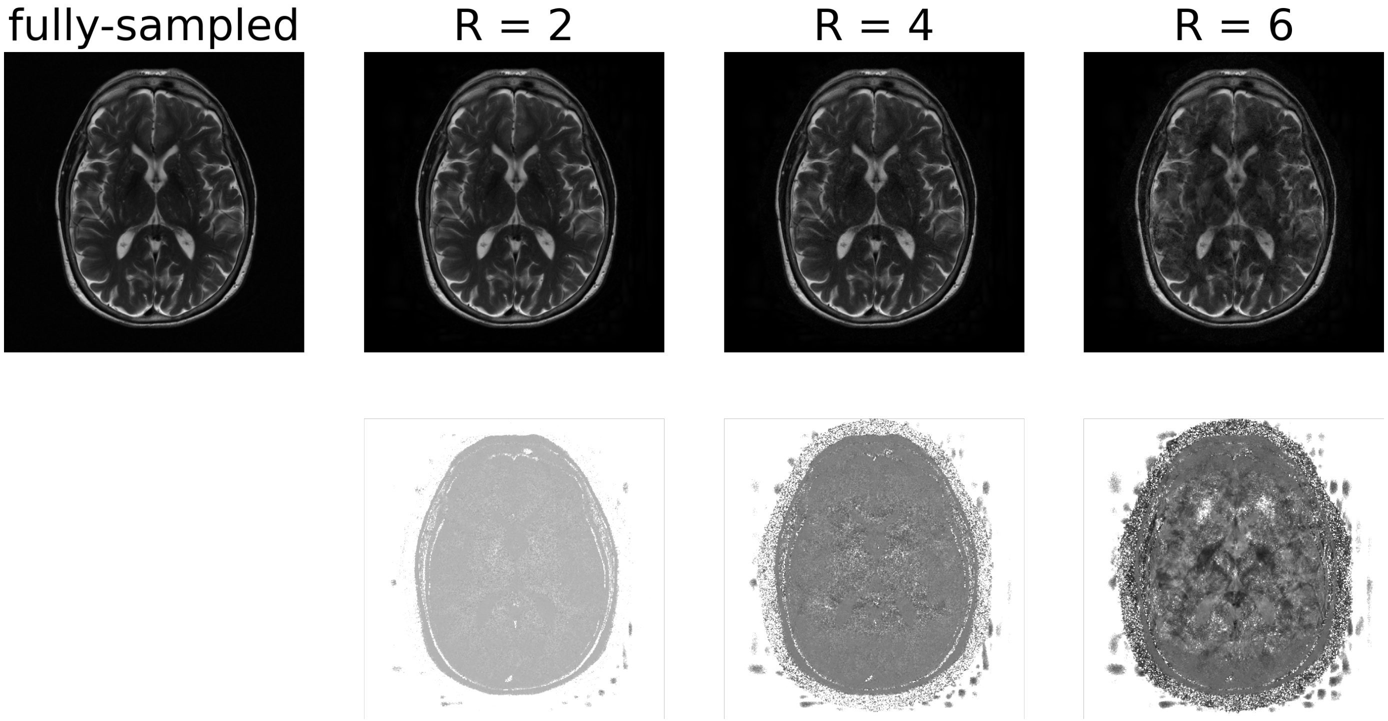
$$(S^* \mathcal{F}_u^{-1} \mathcal{F}_u S + \alpha) x = S^* \mathcal{F}_u^{-1} y \tag{3}$$

- PICS with ℓ^1 regularization:

$$\Phi(x) = \mathrm{argmin}_x \left\| \mathcal{F}_u S x - y \right\|_2^2 + \alpha \left\| T x \right\|_1 \tag{4}$$

[8] https://github.com/mrirecon/bart
[9] https://github.com/mikgroup/sigpy

Compressed Sensing



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3 Deep Learning Image Reconstruction in MRI

Variational Network [10]

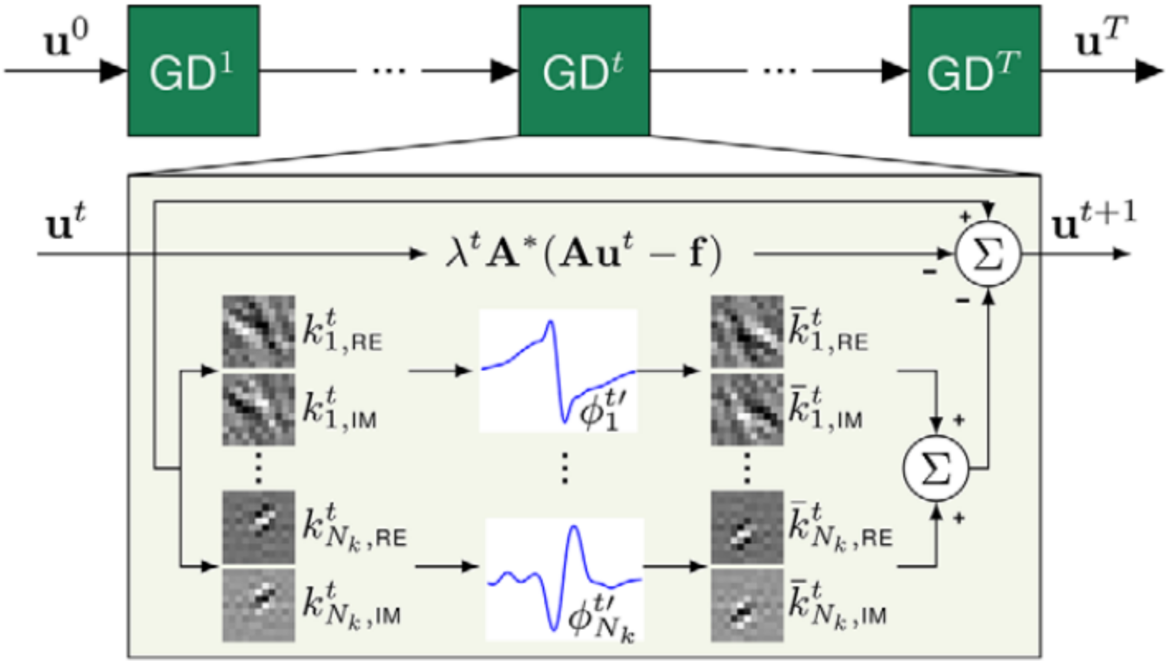
$$\min_u \left\{ \mathcal{R}(u) + \frac{\lambda}{2} \|Au - f\|_2^2 \right\} \tag{5}$$

$$\mathcal{R}(u) = \sum_{i=1}^{N_k} < \Phi_i(K_i u), 1 > \tag{6}$$

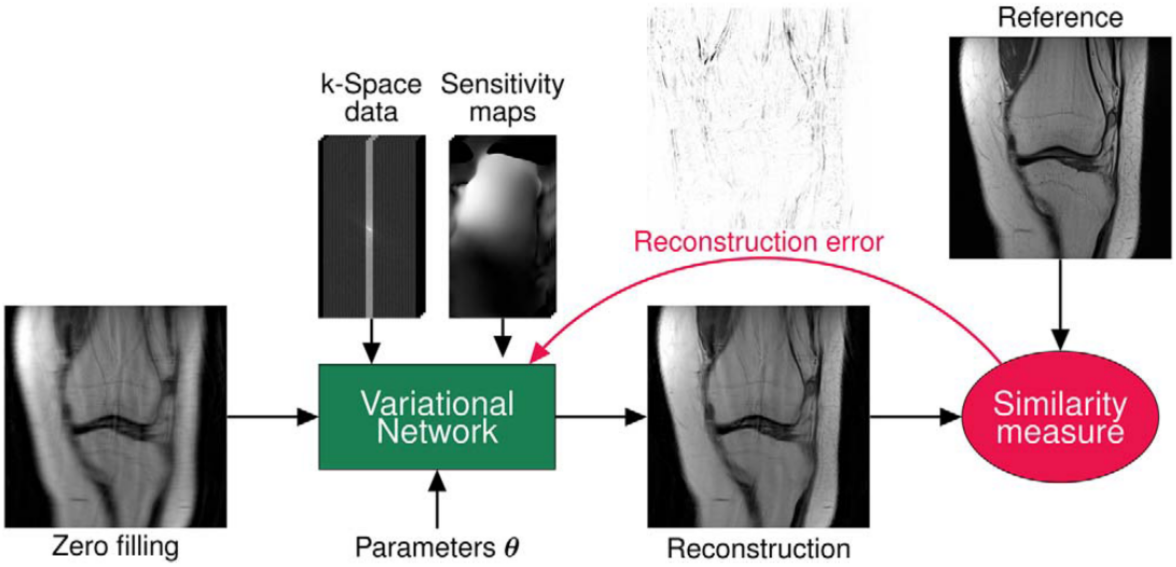
$$u^{(t+1)} = u^{(t)} - \alpha^{(t)} \left(\sum_{i=1}^{N_k} (K_i)^T \Phi_i'(K_i u^{(t)}) + \lambda A^*(Au^{(u)} - f) \right) \tag{7}$$

[10] Hammernik K, et al. Learning a variational network for reconstruction of accelerated MRI data. *Magn Reson Med* (2018).

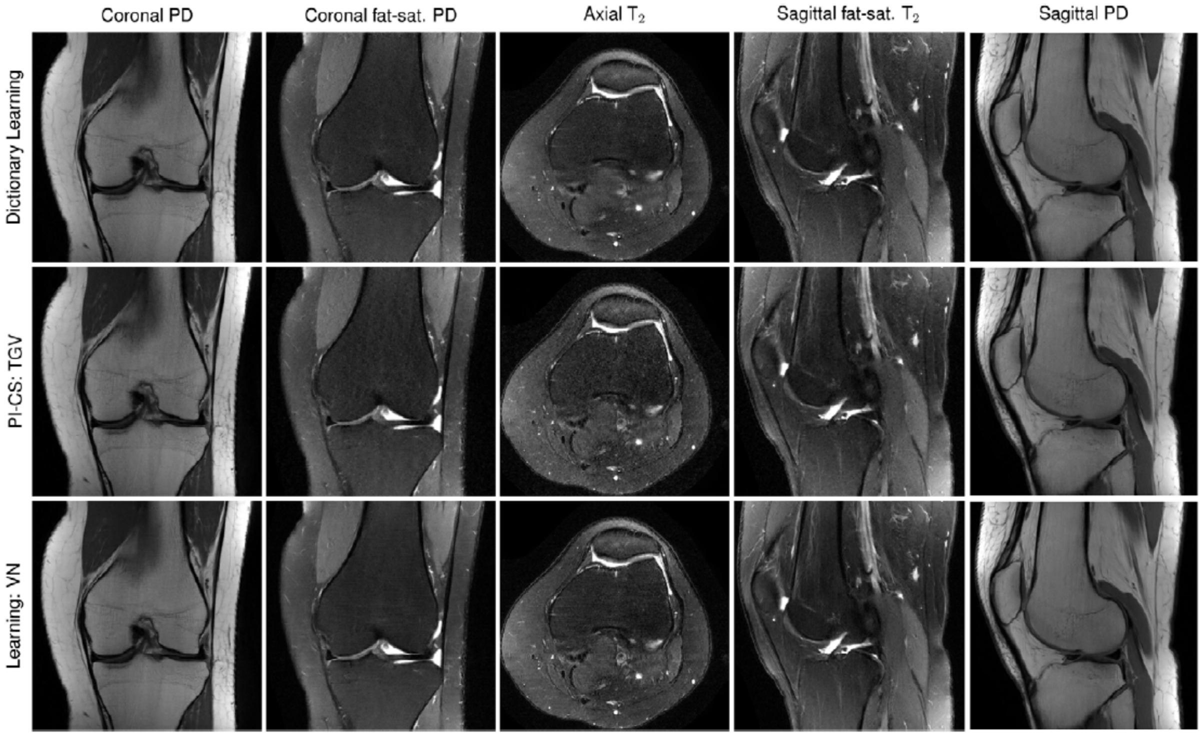
Variational Network



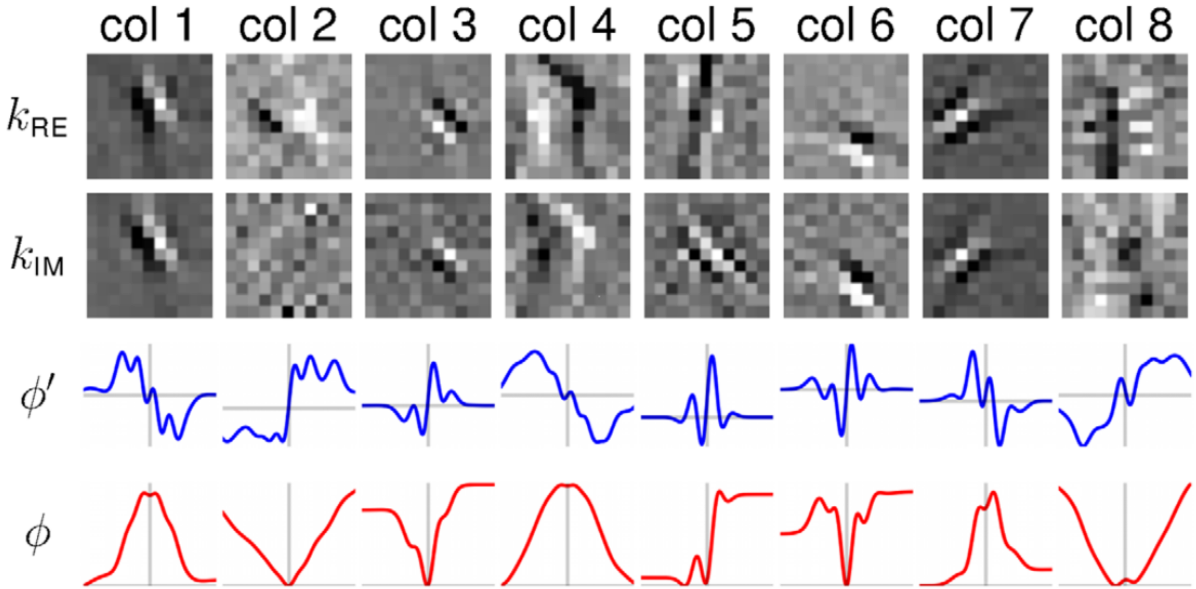
Variational Network



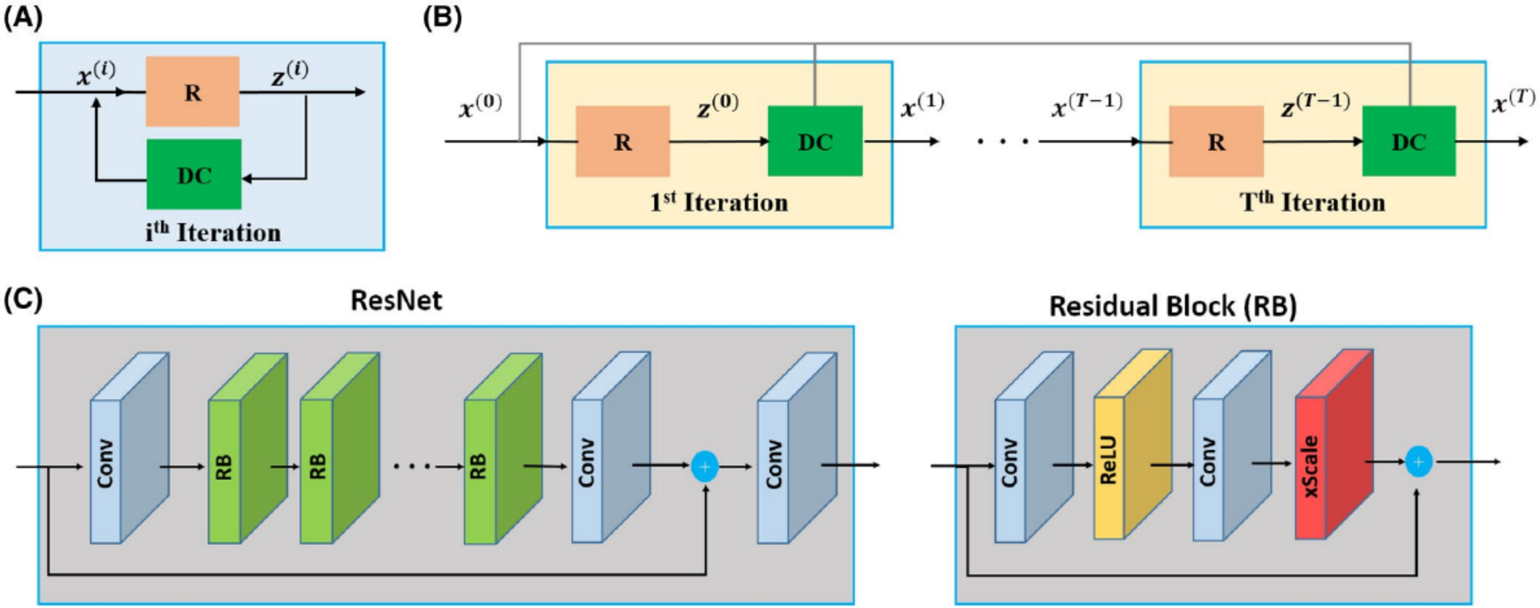
Variational Network



Variational Network

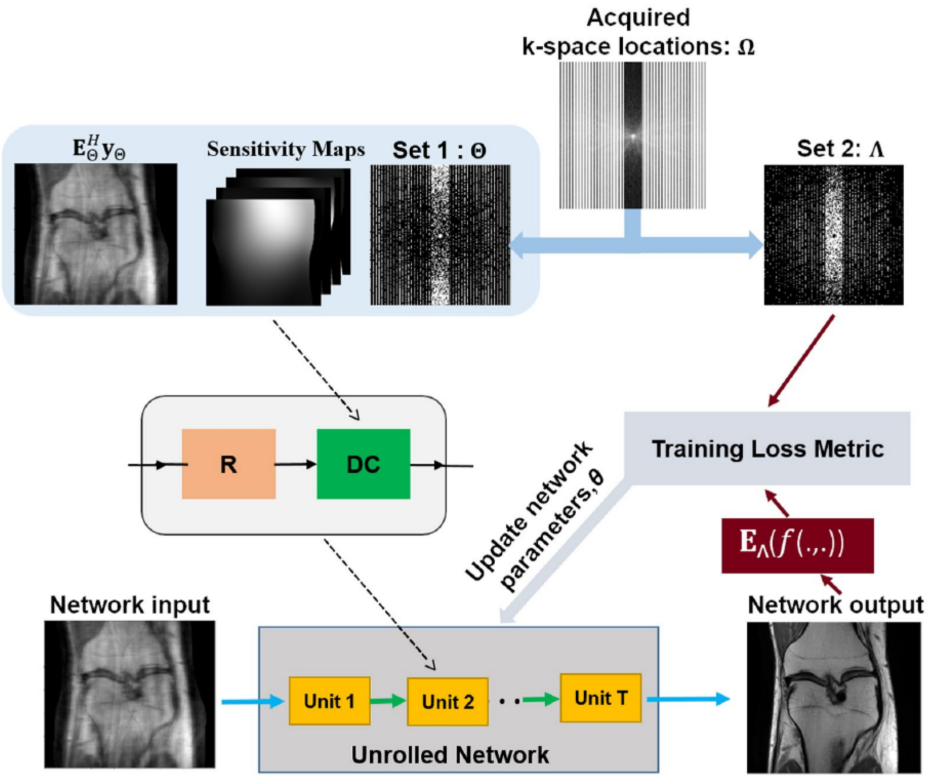


Self-Supervised Learning[11]



[11] Yaman B, et al. Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data. *Magn Reson Med* (2020).

Self-Supervised Learning



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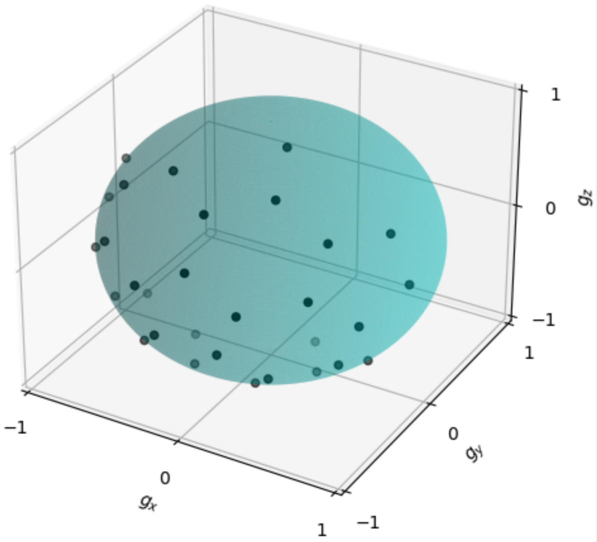
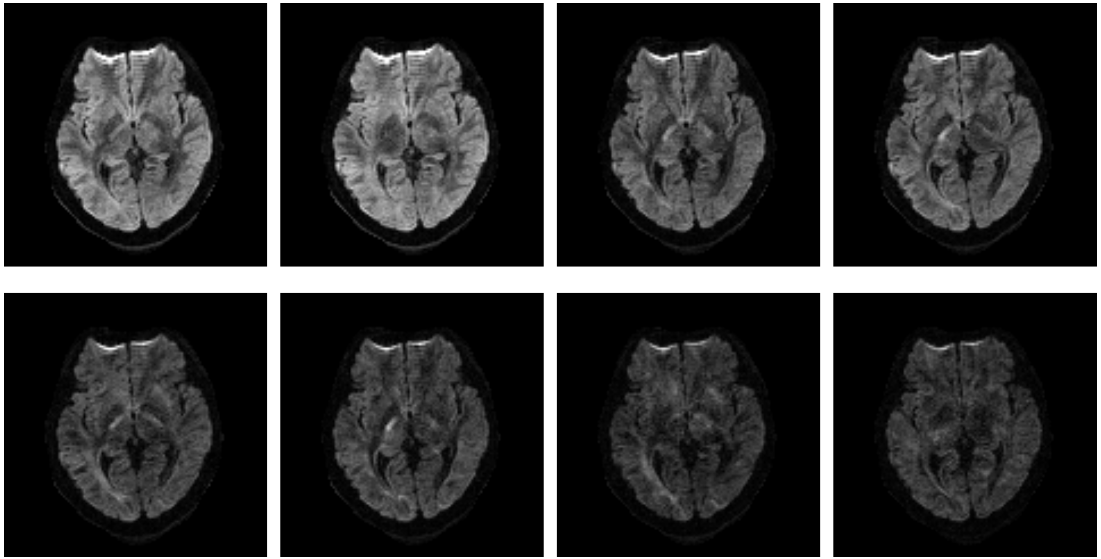
4 Image Reconstruction in Diffusion MRI

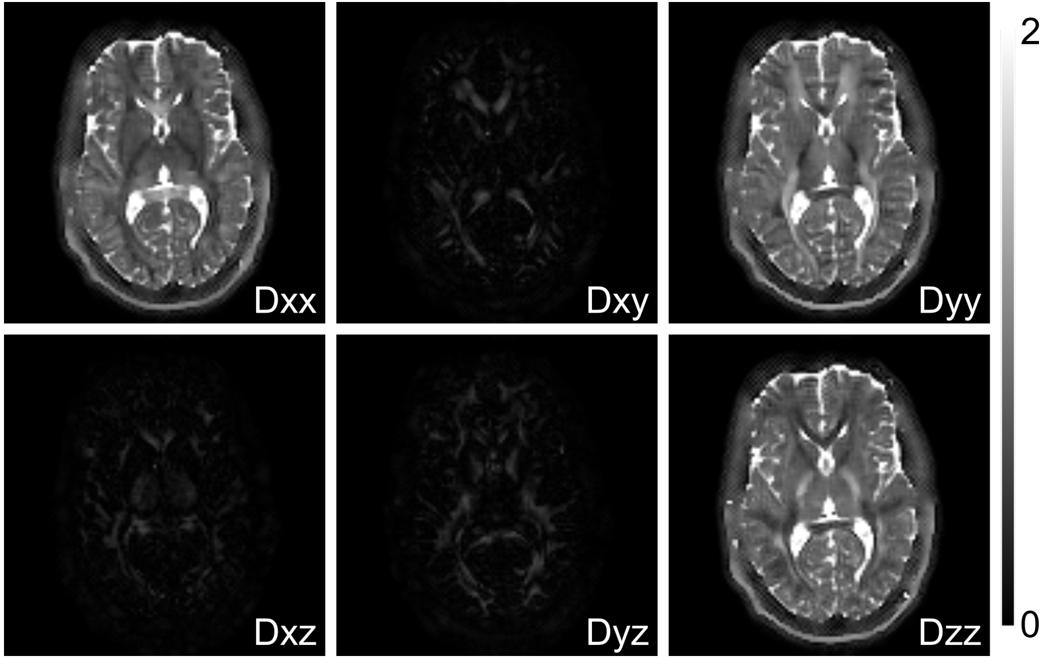
Image Reconstruction in Diffusion MRI: Diffusion-weighted images





- Single-shot EPI diffusion acquisition, 1.5×1.5 mm^2 resolution with in-plane undersampling factor 2, 3 mm slice thickness, $b = 1000, 1000, 2000, 2500\ \mathrm{s/mm^2}$

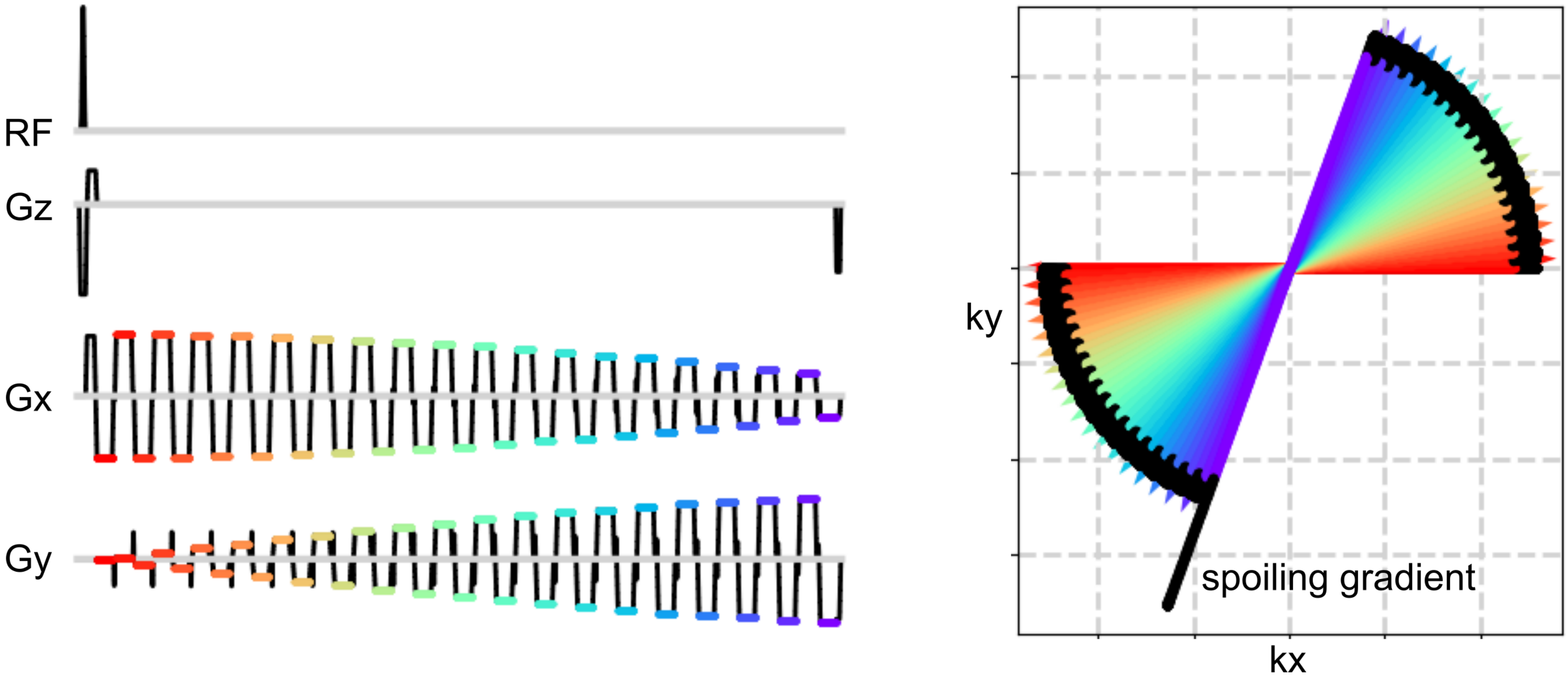
Image Reconstruction in Diffusion MRI: Diffusion Tensors $[\mu\mathrm{m}^2\ \mathrm{ms}^{-1}]$



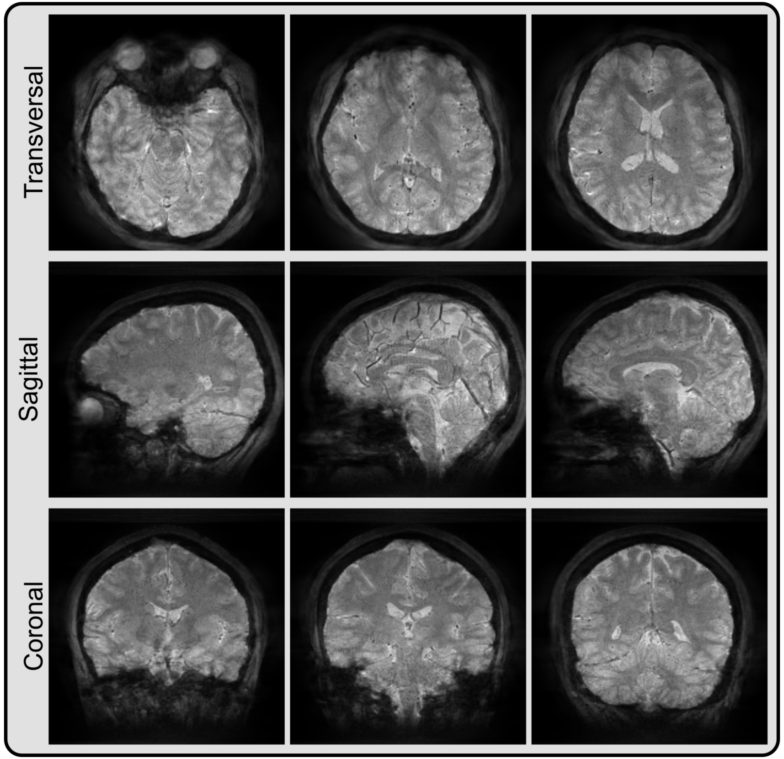
- Single-shot EPI diffusion acquisition, 1.5×1.5 mm^2 in-plane resolution, 3 mm slice thickness. $b = 100, 500, 1000\ \mathrm{s/mm^2}$.

5 Radial Echo-Planar Imaging

Radial Echo-Planar Imaging



Radial Echo-Planar Imaging



6 Summary

Summary

- A brief introduction to MRI
- Developments of image reconstruction in MRI: parallel imaging and compressed sensing
- Deep learning image reconstruction: Variational network
- Diffusion MRI: high-dimensional MRI
- Radial EPI: Combination of motion robustness and distortion free from radial sampling with fast acquisition from EPI

- Computational Imaging Lab of Prof. Dr. Florian Knoll: https://www.cil.tf.fau.de/