

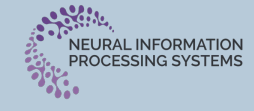


Project Page

# ResoNet: Noise-Trained Physics-Informed MRI Off-Resonance Correction

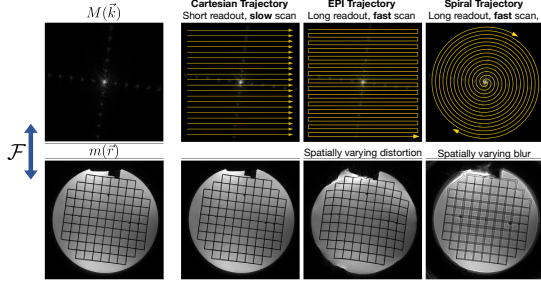
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## Introduction

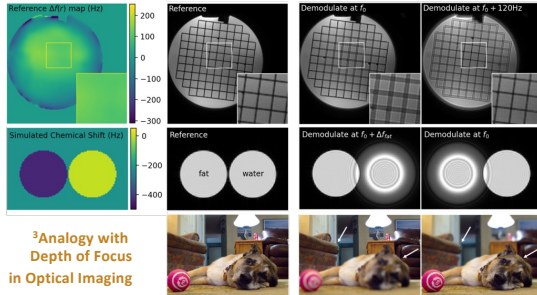
- Magnetic Resonance Imaging (MRI) collects samples in the spatial Fourier domain ( $k$ -space) in many shots, called *readouts*.
- Non-Cartesian trajectories provide rapid imaging<sup>1</sup> and robustness to patient motion<sup>2</sup>, but are more susceptible to *off-resonance* artifacts.



- Goal:** develop a physics-informed deep learning-based reconstruction framework to correct off-resonance in MRI.

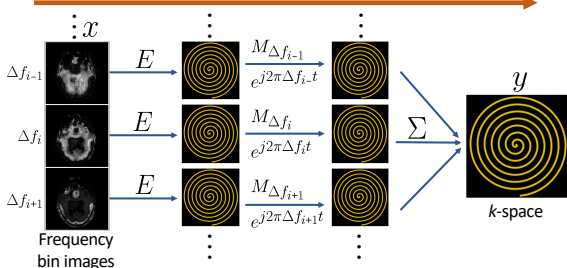
## Off-Resonance Blurring

- Artifacts due to main magnetic field inhomogeneities and tissue properties.



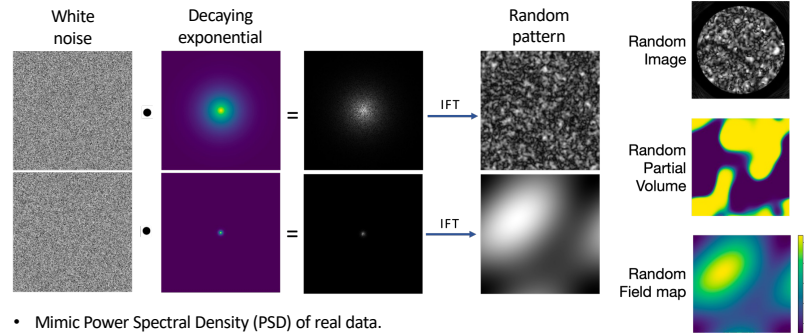
## Physics-Informed Forward Model A

$$A = \sum_i M_{\Delta f_i} E$$



- Model the object as a **stack of sharp images at multiple frequency bins**.
- $E$ : encode (e.g., Non-Uniform FFT).  $M_{\Delta f}$ : phase modulate.  $\Sigma$ : sum across bins.

## Synthetic Noise-Like Training Data

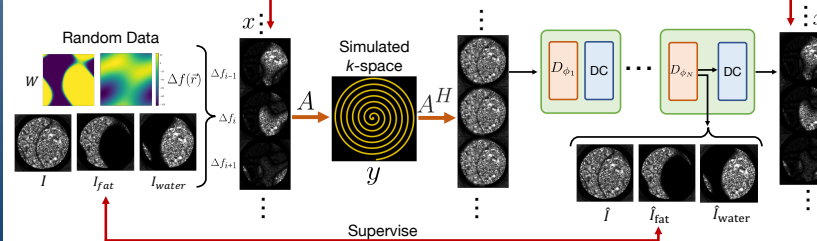


- Mimic Power Spectral Density (PSD) of real data.

## Physics-Informed Deep Learning Framework

- Previous works aim to deblur images directly<sup>4-6</sup> or require/estimate field maps<sup>7-8</sup>.
  - ✗ Neglect the physics during reconstruction<sup>4,6-7</sup>
  - ✗ Rely on training datasets collection<sup>6-8</sup>
  - ✗ Do not handle fat/water partial volume effects<sup>4-8</sup>
  - ✗ Require extra scans<sup>5</sup>
- Our approach:
  - ✓ Model leverages physics model  $A$  and deep learning to reconstruct images.
  - ✓ Correct off-resonance and handle fat/water separation from a single echo-time Spiral scan.

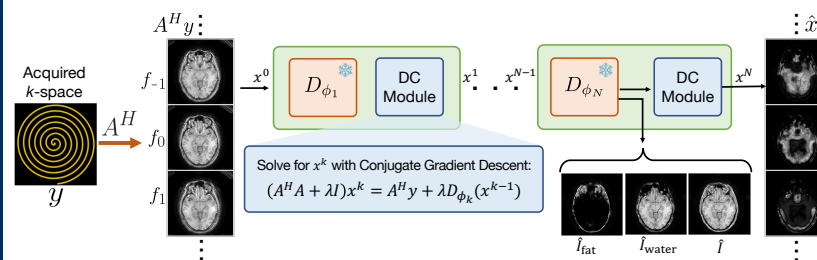
### Training stage



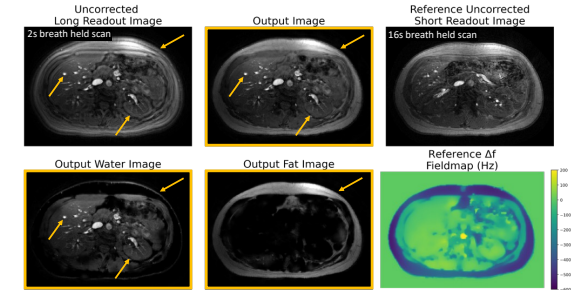
- ✓ Train model exclusively on synthetic noise-like data. Bypass dataset collection challenges.

### Inference stage

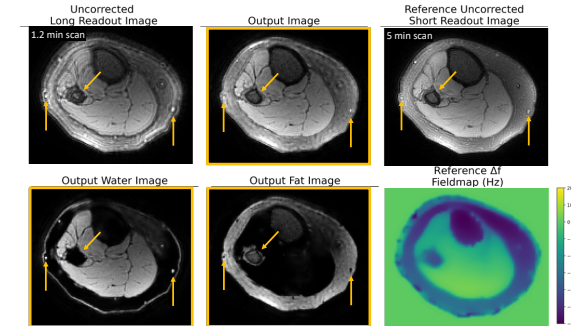
- ✓ Generalize to diverse anatomies and contrasts without retraining. Freeze  $D_{\phi_1}$ .



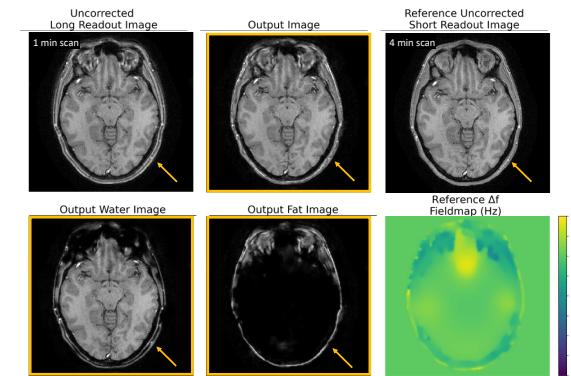
## In-Vivo Results: T1-Weighted Abdominal



## In-Vivo Results: Proton Density-Weighted Knee



## In-Vivo Results: T1-Weighted Brain



## References

[1] M. A. Bernstein, K. F. King, X. J. Zhou, Handbook of MRI pulse sequences. Elsevier, 2004. [2] Y. Yang et al., "Comparison of fast MR scan techniques for cerebral activation studies at 1.5 Tesla," Magn Reson Med, vol. 39, no. 1, pp. 61–67, Jan 1998. [3] Wikimedia Foundation, "Light field camera," Wikipedia, Oct 8, 2022, https://en.wikipedia.org/wiki/Light\_field\_camera. [4] Noll DC et al. Deblurring for non-2D Fourier transform magnetic resonance imaging. 1992. [5] Noll DC et al. Conjugate phase MRI reconstruction with spatially variant sample density correction. 2005. [6] Zeng DY et al. Deep residual network for off-resonance artifact correction with application to pediatric body MRI with 3D cones. Magn Reson Med. 2019. [7] Lim Y et al. Deblurring for spiral real-time MRI using convolutional neural networks. Magn Reson Med. 2020. [8] Haskell MW et al. Deep learning field map estimation with model-based image reconstruction for off-resonance correction of brain images using a spiral acquisition. ISMRM Workshop on Data Sampling and Image Reconstruction. 2020.