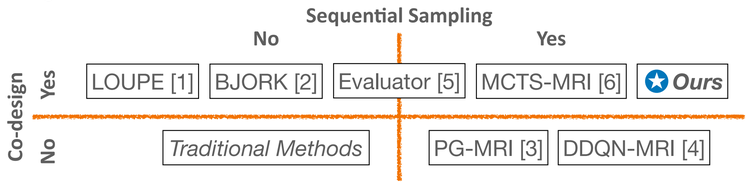
End-to-End Sequential Sampling and Reconstruction for MR Imaging

Tianwei Yin*,2, Zihui Wu*,1, He Sun[1], Adrian V. Dalca[3,4], Yisong Yue[1], Katherine L. Bouman[1]

[1]Caltech, [2]UT Austin, [3]Harvard Medical School, [4]MIT, *Equal contribution

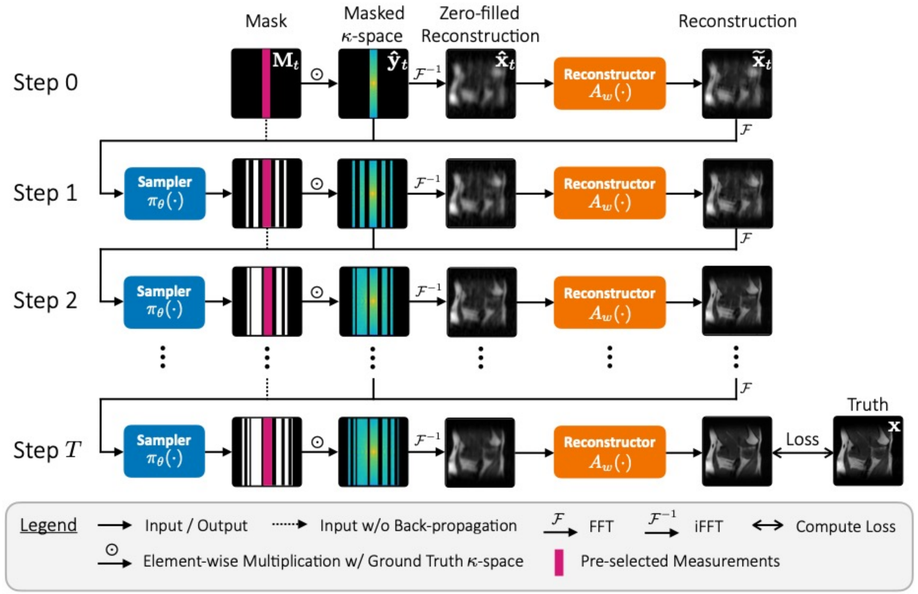
Introduction

- Accelerated MRI expedites the acquisition process by subsampling the κ-space. Reconstruction methods are then used to recover an image from the sparse κ-space measurements.
- Previous work took either a **co-design** approach to jointly optimize a sampler and a reconstructor or a **sequential sampling** approach to adaptively generate customized sampling patterns for each subject rather than using a fixed pattern for better performance.
- Our proposed model successfully combines the advantages of sequential sampling and co-design.



Method

- Sequentially acquire the next best set of measurements based on intermediate information
- Sampler-reconstructor co-design is achieved through end-to-end training

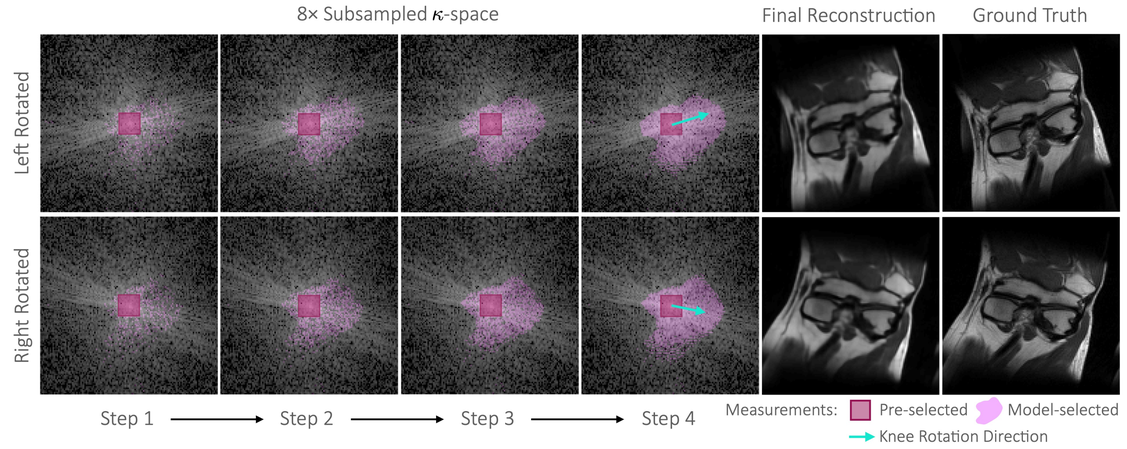


References

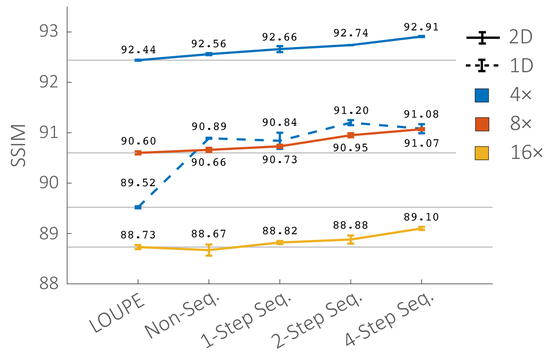
[1]: Deep-learning-based Optimization of the Under-sampling Pattern in MRI (Bahadir et al., 2020)
[2]: B-spline Parameterized Joint Optimization of Reconstruction and K-space Trajectories (BJORK) for Accelerated 2D MRI (Wang et al., 2021)
[3]: Experimental Design for MRI by Greedy Policy Search (Bakker et al., 2020)
[4]: Active MR k-space Sampling with Reinforcement Learning (Pineda et al., 2020)
[5]: Reducing Uncertainty in Undersampled MRI Reconstruction with Active Acquisition (Zhang et al., 2019)
[6]: Self-Supervised Deep Active Accelerated MRI (Jin et al., 2019)

Experiments

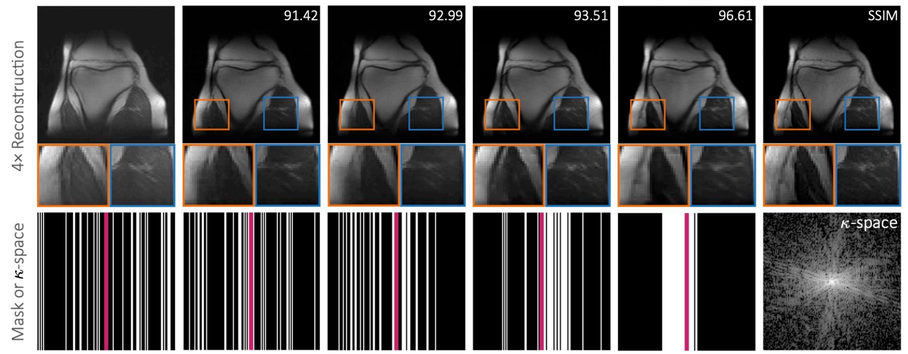
- Our model shows adaptiveness to different input images (see the right figure). The final sampling patterns in the fourth column contain visible directional structure that aligns with the κ-space power spectrum. Rotated anatomical images, such as these rotated knee images, were *not* included in the training set (or quantitatively evaluated test set).



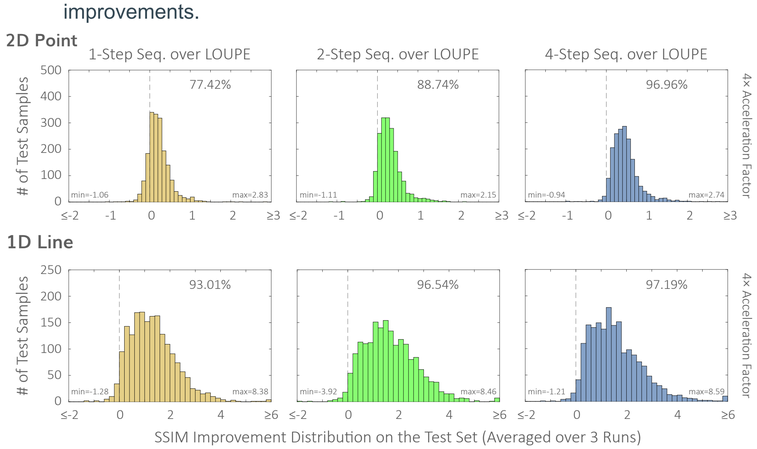
- Quantitative comparisons with the previous state-of-the-art baseline, LOUPE [1], under various sampling scenarios and acceleration factors



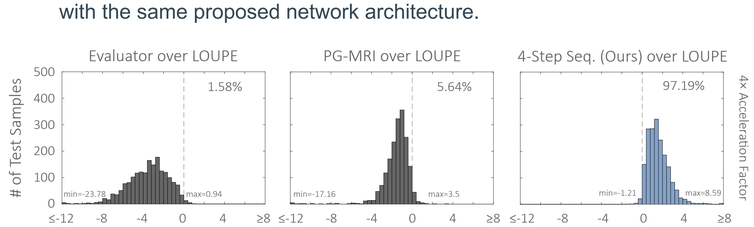
- Visual comparisons with the previous state-of-the-art LOUPE [1] and a few other common baselines [3], [5] under the 4x accelerated 1D line sampling scenario



- Sequential sampling provides significantly improvements upon a fixed sampling pattern. More sequential steps consistently lead to larger improvements.



- Gradient-based co-design is crucial for good performance. It allows us to significantly outperform models that use fixed reconstructors, even those with the same proposed network architecture.



Co-design	1-Step Seq.	4-Step Seq.
Yes	**92.66 ± 0.06**	**92.91 ± 0.01**
No	90.33 ± 0.01	90.40 ± 0.02

Scan this QR code for more details on our project website!