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LEADERS: Learnable Deep Radial Subsampling for MRI reconstruction

IEEE ISBI 2022
International Symposium on Biomedical Imaging
28-31 March 2022, ITC Royal Bengal, Kolkata, India

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Motivations

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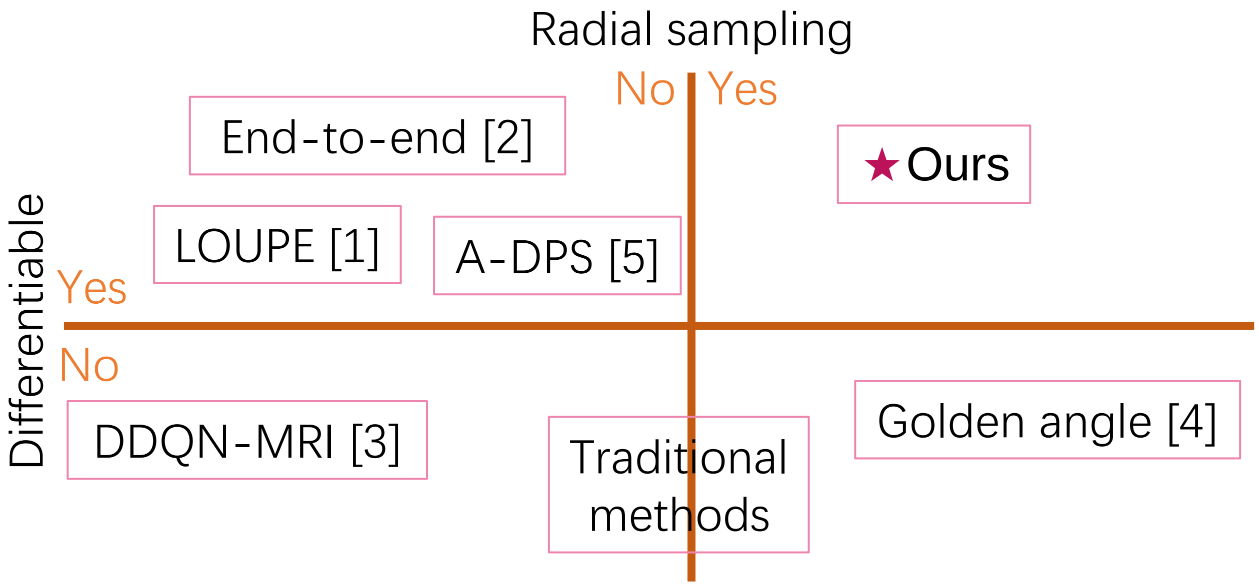
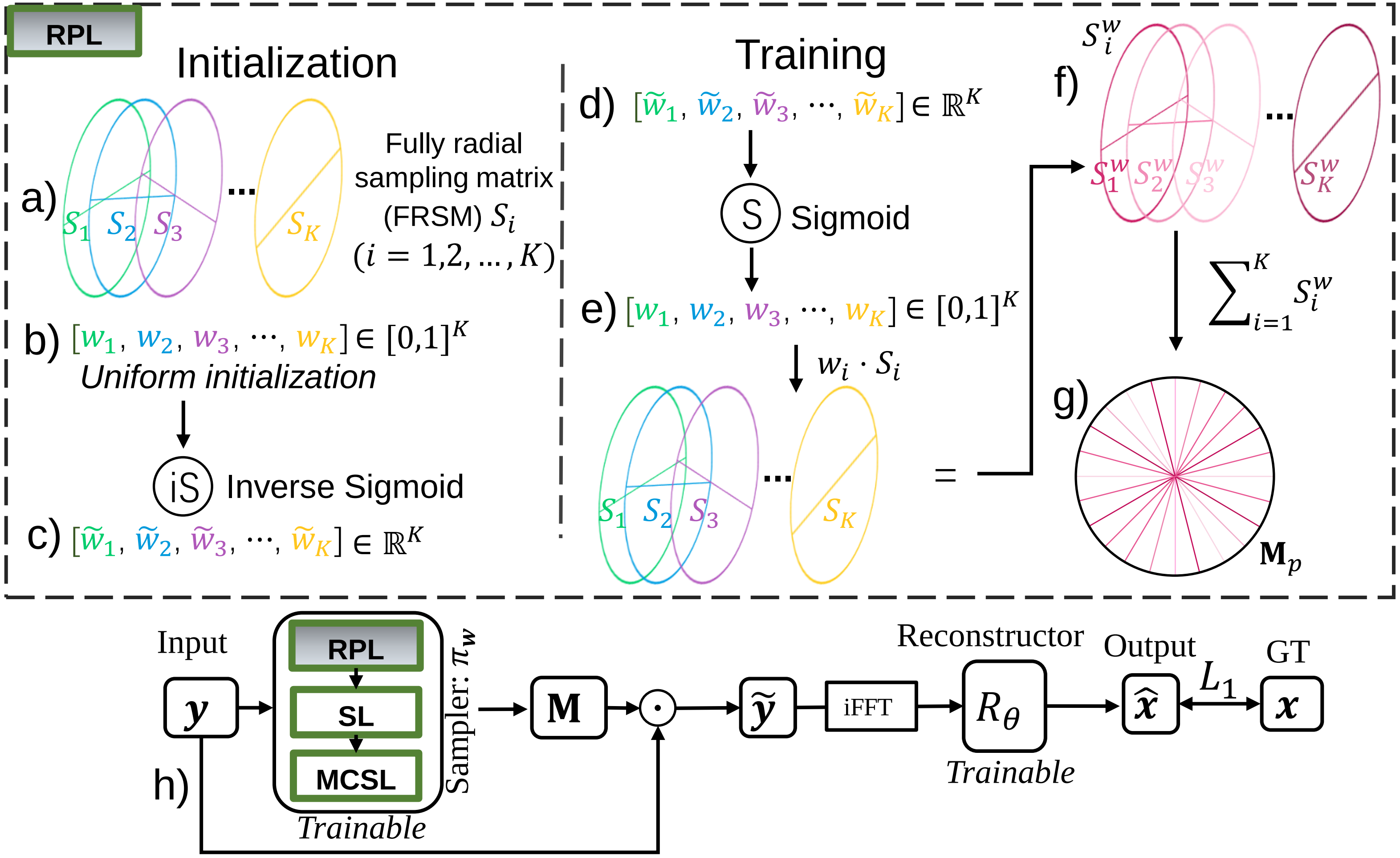
- Suitable subsampling is crucial for MRI reconstruction. So far, all of deep subsampling methods focus on Cartesian sampling scenarios.
- Radial subsampling design: generate adaptive radial sampling trajectories for each subsampling rate by a deep Monte Carlo method.

Related works



- [1] Deep-learning-based Optimization of the Under-Sampling Pattern in MRI (Bahadir et al, 2020)
- [2] End-to-End Sequential Sampling and Reconstruction for MR Imaging (Tianwei et al, 2021)
- [3] Active MR k-space Sampling with Reinforcement Learning (Pineda et al, 2020)
- [4] An Optimal Radial Profile Order-based on the Golden Ratio for Time-resolved MRI (Winkelmann et al, 2006)
- [5] Active Deep Probabilistic Subsampling (Hans et al, 2021)

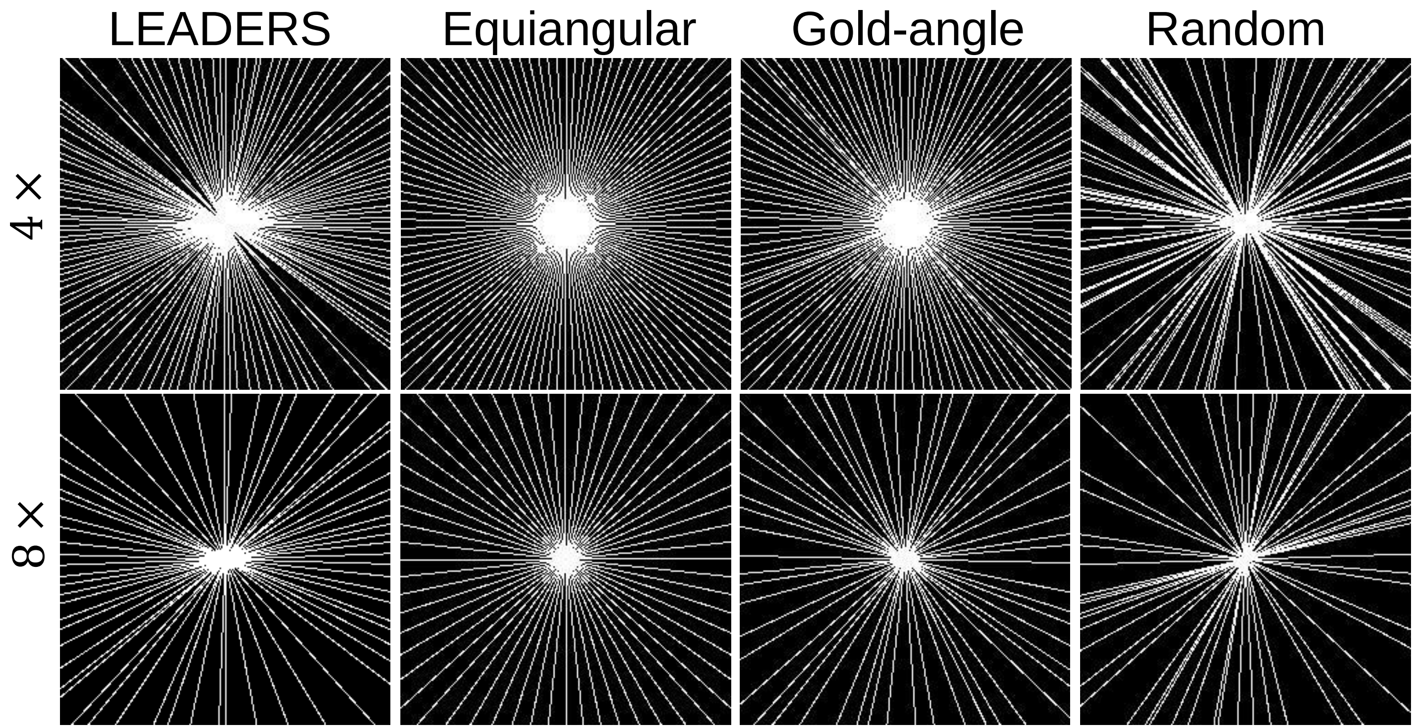
Method

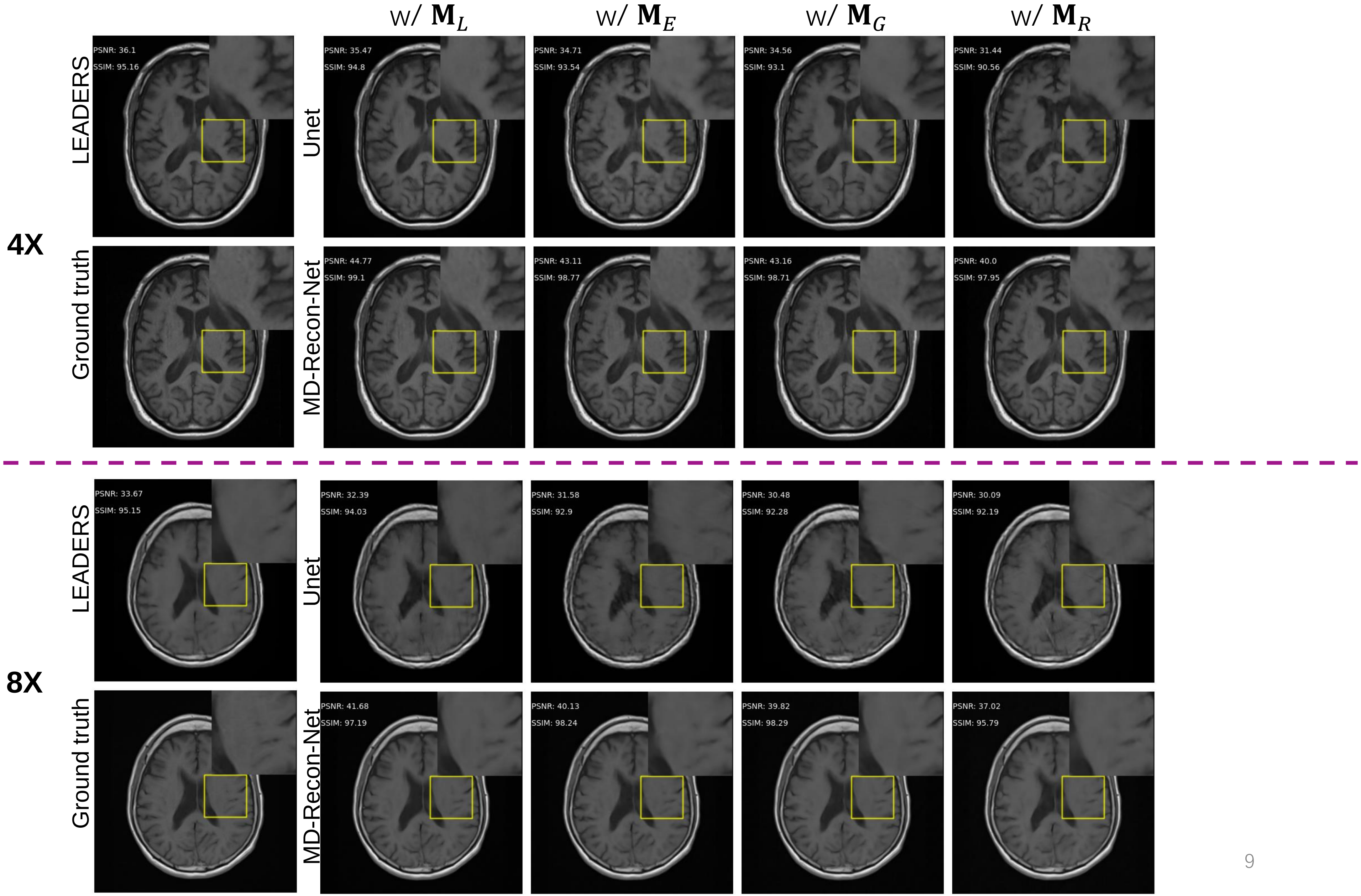


Radial parameter layer (RPL):
Initialization: a)~b)
Forward training: d)~g)

Radial sampler and reconstructor are optimized jointly:
1st stage: Training sampler and reconstructor jointly;
2nd stage: Fixing sampler, binarizing its' output, and finetuning reconstructor.

Experiments





w/ $\mathbf{M}_L$
w/ $\mathbf{M}_E$
w/ $\mathbf{M}_G$
w/ $\mathbf{M}_R$
4X
LEADERS
PSNR: 36.1
SSIM: 95.16
Unet
PSNR: 35.47
SSIM: 94.8
PSNR: 34.71
SSIM: 93.54
PSNR: 34.56
SSIM: 93.1
PSNR: 31.44
SSIM: 90.56
Ground truth
MD-Recon-Net
PSNR: 44.77
SSIM: 99.1
PSNR: 43.11
SSIM: 98.77
PSNR: 43.16
SSIM: 98.71
PSNR: 40.0
SSIM: 97.95
8X
LEADERS
PSNR: 33.67
SSIM: 95.15
Unet
PSNR: 32.39
SSIM: 94.03
PSNR: 31.58
SSIM: 92.9
PSNR: 30.48
SSIM: 92.28
PSNR: 30.09
SSIM: 92.19
Ground truth
MD-Recon-Net
PSNR: 41.68
SSIM: 97.19
PSNR: 40.13
SSIM: 98.24
PSNR: 39.82
SSIM: 98.29
PSNR: 37.02
SSIM: 95.79

Experiments

Table 1. Quantitative results with two acceleration factors

R	Model	Radial subsampling patterns			
		$\mathbf{M}_L$	$\mathbf{M}_E$	$\mathbf{M}_G$	$\mathbf{M}_R$
		PSNR	PSNR	PSNR	PSNR
4×	Unet [16]	**35.03**	34.14	33.76	32.91
	MDR [19]	**42.41**	40.50	40.49	38.42
	Our	**35.73**	-	-	-
8×	Unet [16]	**39.55**	38.97	39.03	35.31
	MDR [19]	**47.02**	46.46	46.01	42.87
	Our	**40.31**	-	-	-

MDR: MD-Recon-Net

Deep radial subsampling is crucial for good performance.

- **4x accelerated rate in the 1st row.**
- **8x accelerated rate in the 2nd row.**

[16] U-net: Convolutional Networks for Biomedical Image Segmentation (Ronneberger et al, 2015)
[19] MD-Recon-Net: A Parallel Dual-domain Convolutional Neural Network for Compressed Sensing MRI (Maosong et al, 2020)

Conclusion

This paper proposed:

1. The first pipeline of learning radial subsampling, reconstruction simultaneously
2. A new state of the art model
3. Matching a MRI reconstruction model well with a suitable radial trajectories.

Thank you!

Code: https://github.com/Deep-Imaging-Group/LEADERS