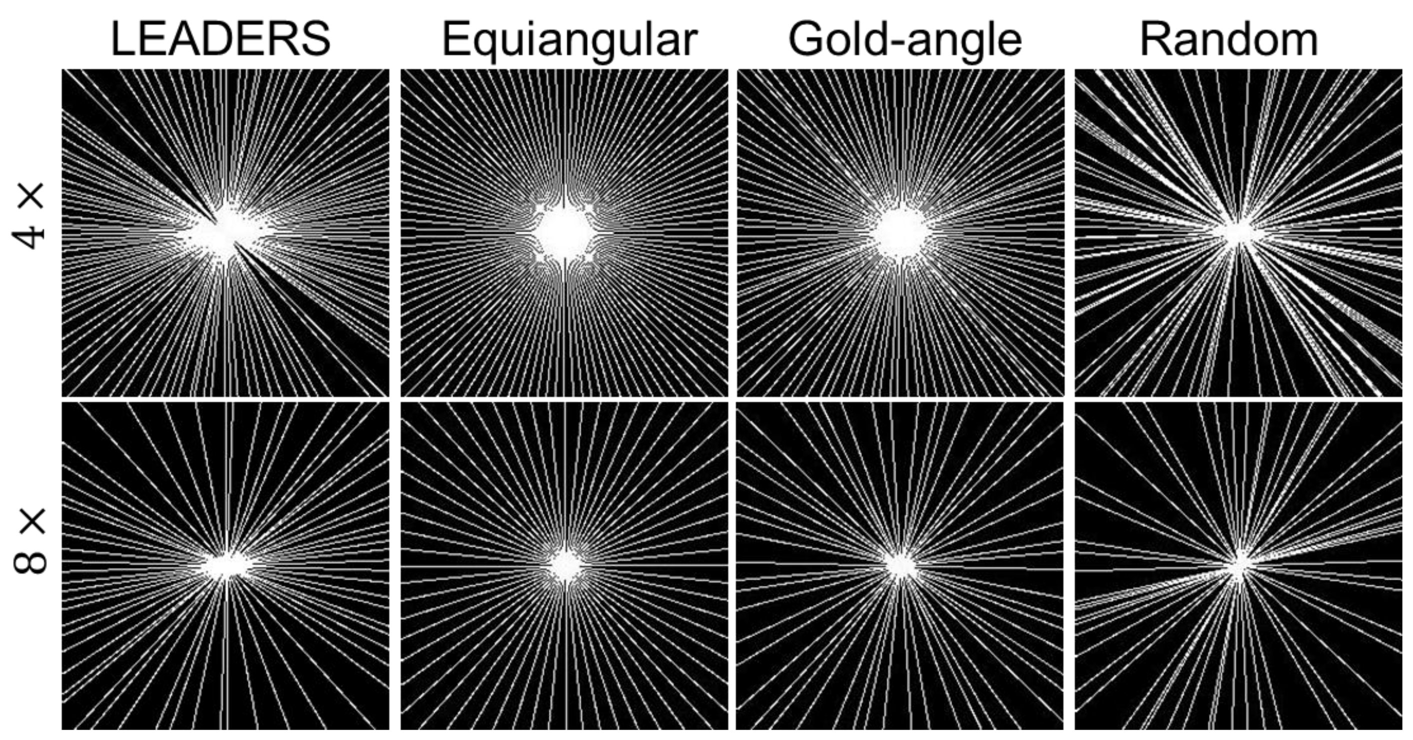
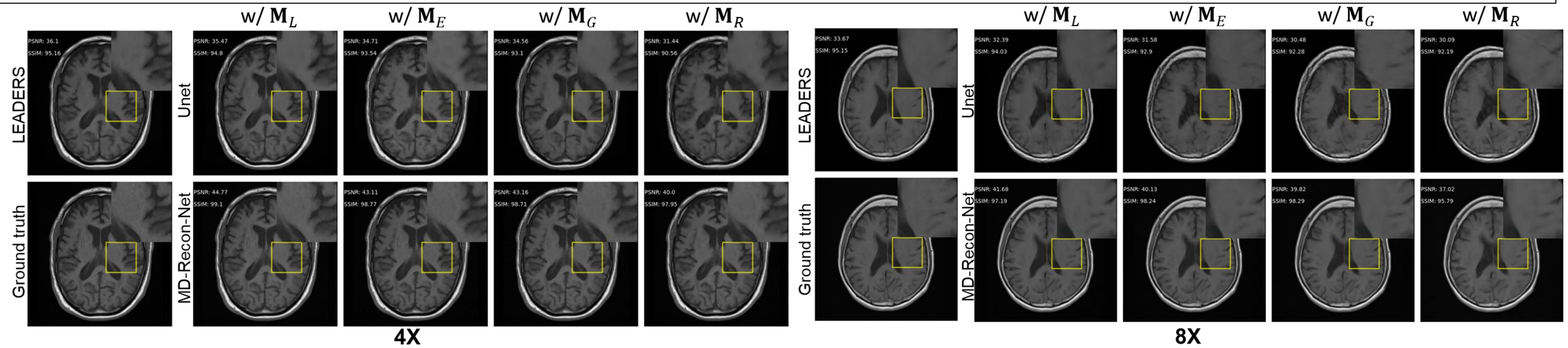
LEADERS: Learnable Deep Radial Subsampling for MRI reconstruction

Zhiwen Wang[1], Bowen Li[1], Wenjun Xia[1], Chenyu Shen[1], Mingzheng Hou[2,1], Hu Chen[1], Yan Liu[3], Jiliu Zhou[1], Yi Zhang[4, 1, ✉]
[1]College of Computer Science, Sichuan University, Chengdu, China
[2]National Key Laboratory of Fundamental Science on Synthetic Vision, Sichuan University, Chengdu, China
[3]College of Electrical Engineering , Sichuan University, Chengdu, China
[4]School of Cyber Science and Engineering, Sichuan University, Chengdu, China

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

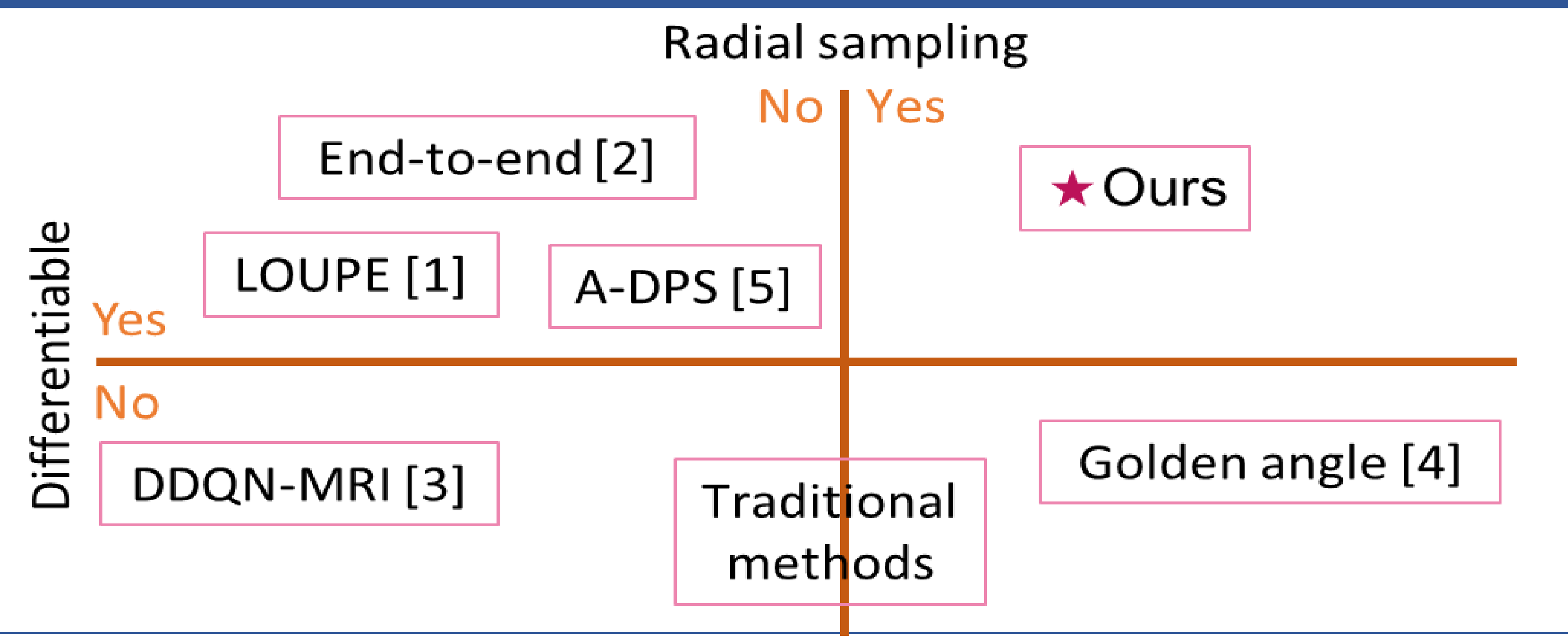




Motivations

- MRI suffers from a relatively long acquisition time, which limits its sphere of application and probably discomfort the patients.
- One way to speed up MR imaging is to observe partial measurement and reconstruct image.
- Radial subsampling design: generate adaptive radial sampling trajectories for each subsampling rate by deep Monte Carlo method.

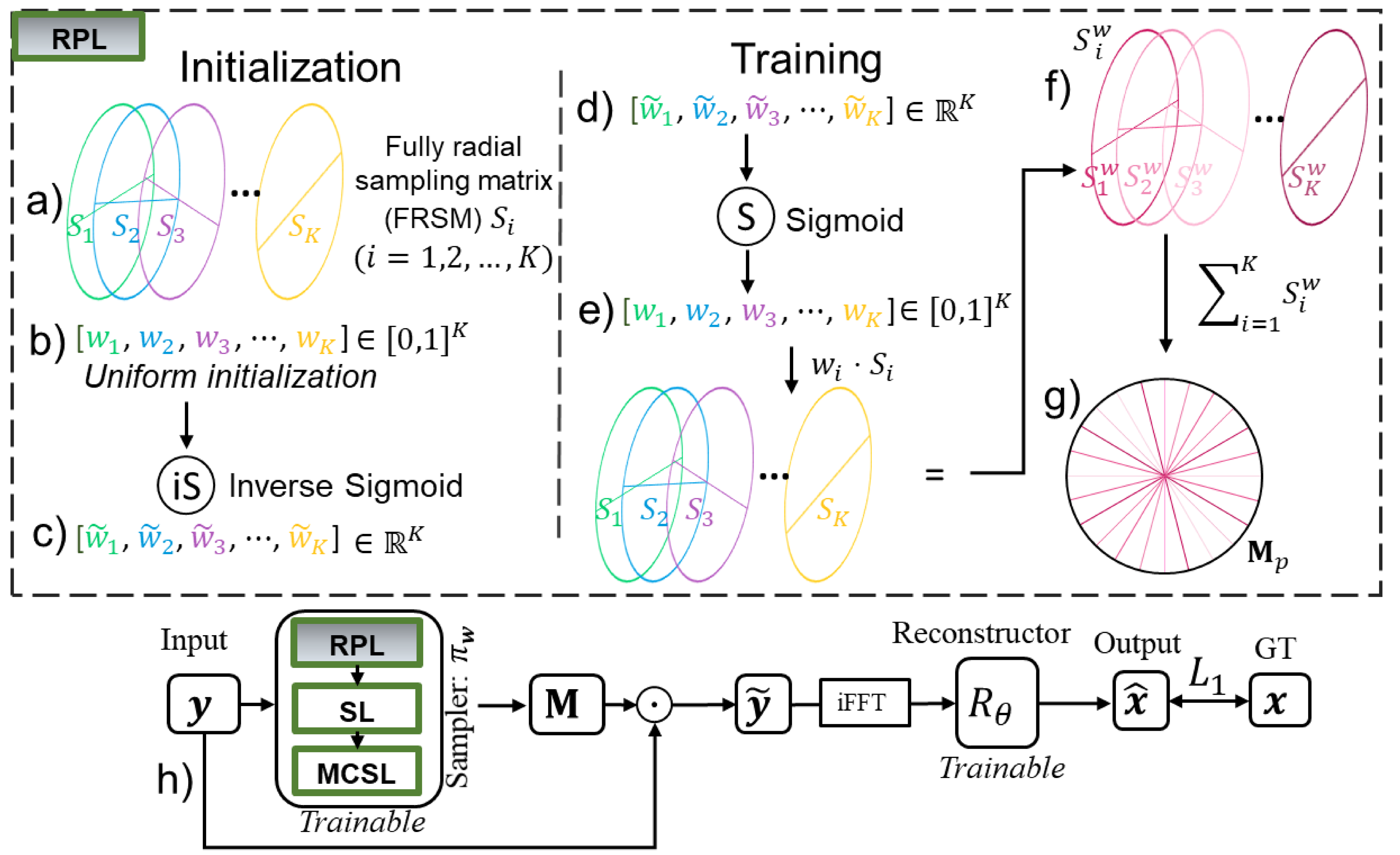
Related works



References

- [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 Orderbased on the Golden Ratio for Time-resolved MRI (Winkelmann et al, 2006)
- [5] Active Deep Probabilistic Subsampling (Hans et al, 2021)

Method (Simplified)



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

Table 1. Quantitative results with two acceleration factors

R	Model	$\mathbf{M}_L$ PSNR	$\mathbf{M}_E$ PSNR	$\mathbf{M}_G$ PSNR	$\mathbf{M}_R$ PSNR
		Radial subsampling patterns			
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)