P204: Zero-Shot Self-Supervised Joint Temporal Image and Sensitivity Map Reconstruction via Linear Latent Space

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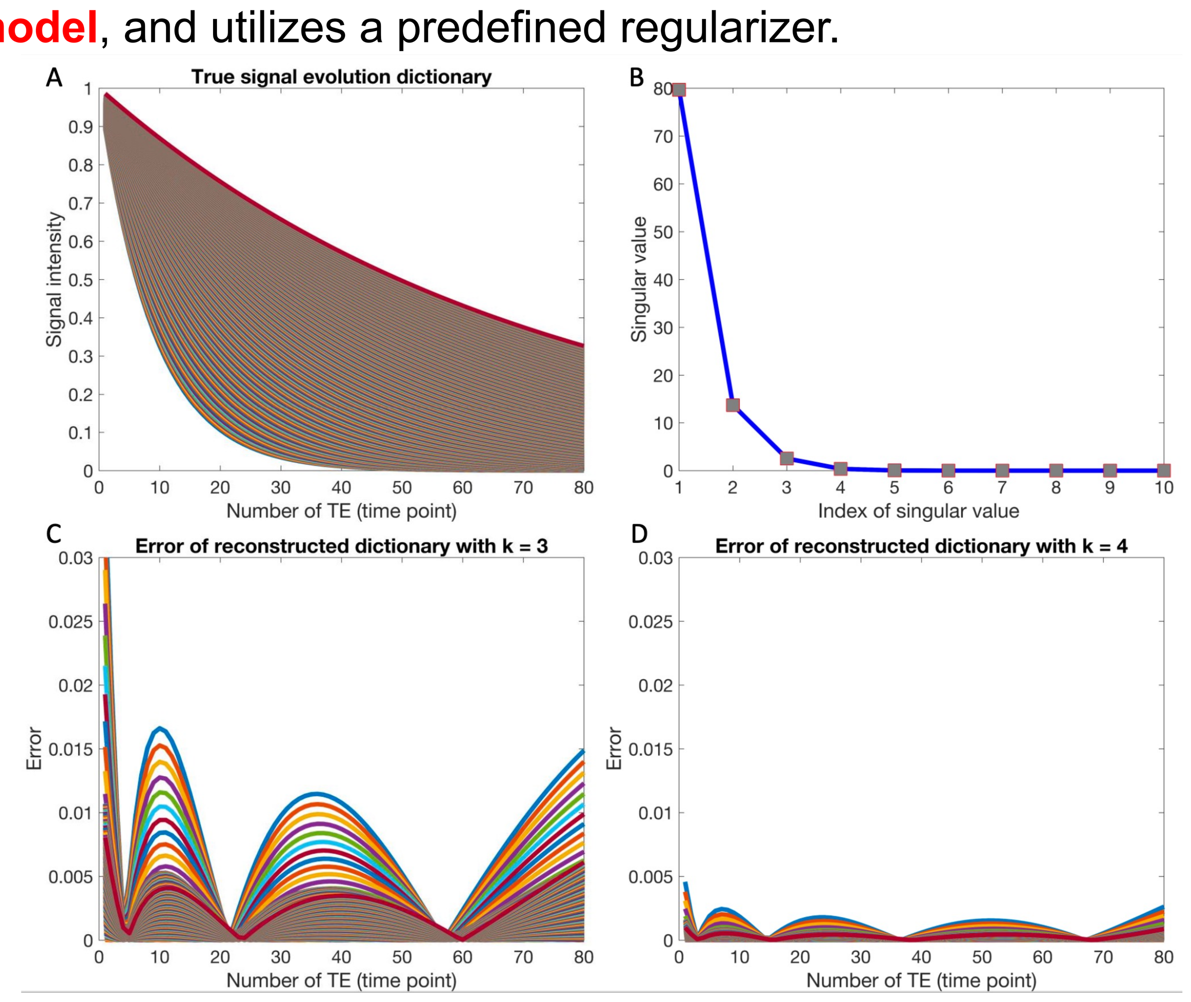
Abstract

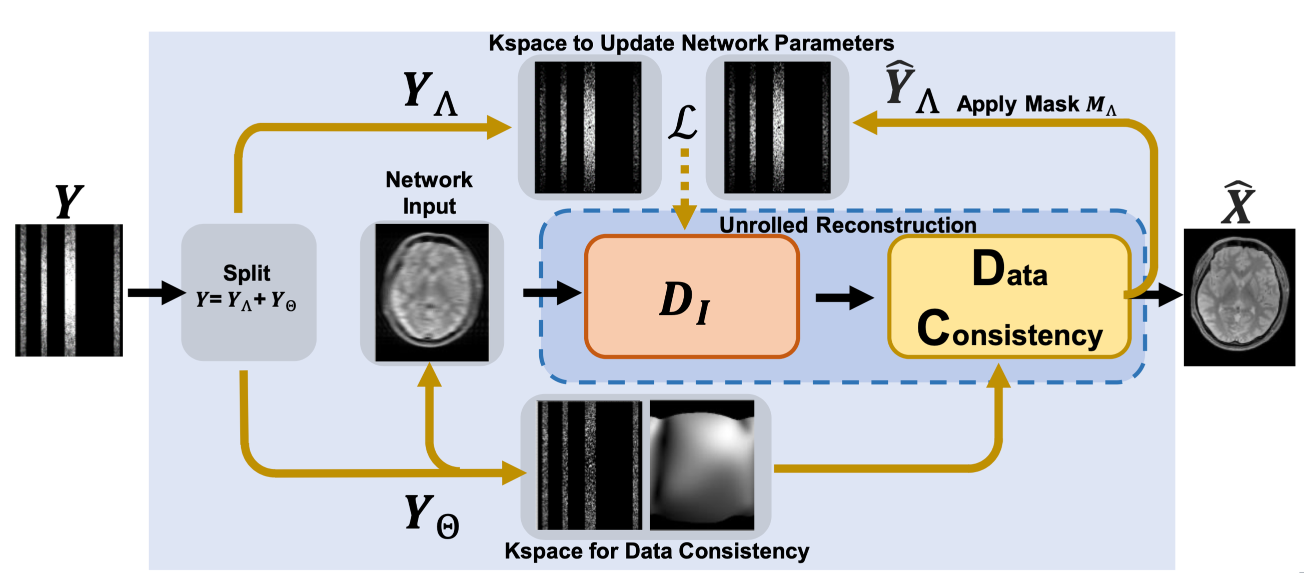
- T2-shuffling is widely used to resolve temporal signal dynamics in FSE acquisitions via **linear latent space** and a **predefined regularizer**.
- Recent self-supervised learning methods in an unrolled manner achieve high-fidelity reconstructions by learning a regularizer from the undersampled data without a standard supervised training data set.
- In this work, we propose a novel approach that utilizes a self supervised learning framework to **learn a regularizer constrained on a linear latent space** which improves time-resolved FSE images reconstruction quality. Additionally, in regimes without groundtruth sensitivity maps, we propose **joint estimation of coil-sensitivity maps** using an iterative reconstruction technique.
- We perform experiments on **simulated** and **retrospective in-vivo data** to evaluate the performance of the proposed zero-shot learning method for temporal FSE reconstruction.

Introduction

- T2-shuffling has demonstrated success in resolving temporal images from volumetric FSE acquisitions which exploits temporal correlations with **a low-dimensional subspace model**, and utilizes a predefined regularizer.

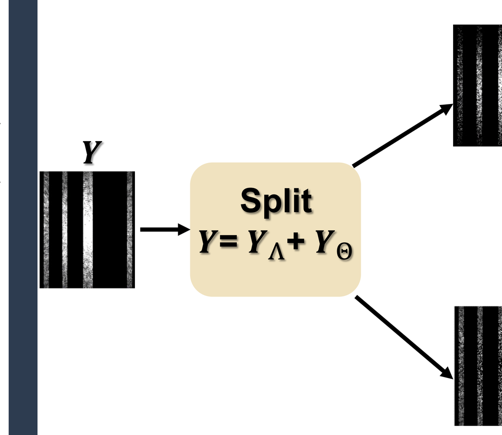


- To train models without ground truth, Yaman et al. proposed a **self-supervised learning reconstruction method** (SSDU), which trains models in a self-supervised fashion by partitioning under-sampled kspace data into two disjoint sets, Θ and Λ, and training a network as a regularizer in the traditional optimizations with the information from Θ to predict the unseen data, Λ.



Methodology

Self-supervised reconstruction for single image



$$\mathcal{L}(\mathbf{u}, \mathbf{v}) = \frac{\|\mathbf{u}-\mathbf{v}\|_2}{\|\mathbf{u}\|_2} + \frac{\|\mathbf{u}-\mathbf{v}\|_1}{\|\mathbf{u}\|_1}$$

$\mathbf{Y}_\Lambda$ $\quad$ $\mathbf{M}_\Lambda\mathbf{FS}\hat{\mathbf{X}}$

update

$$\mathbf{Z}^{(i-1)} = \mathcal{D}_\mathbf{I}\left(\mathbf{X}^{(i-1)}\right)$$

$$\begin{aligned}\mathbf{X}^{(i)} &= \arg\min_{\mathbf{X}} \|\mathbf{Y}_\Theta - \mathbf{M}_\Theta\mathbf{FSX}\|_2^2 + \mu\left\|\mathbf{X} - \mathbf{Z}^{(i-1)}\right\|_2^2 \\ &= \left((\mathbf{M}_\Theta\mathbf{FS})^H(\mathbf{M}_\Theta\mathbf{FS}) + \mu\mathbf{I}\right)^{-1}\left((\mathbf{M}_\Theta\mathbf{FS})^H\mathbf{Y}_\Theta + \mu\mathbf{Z}^{(i-1)}\right)\end{aligned}$$

Self-supervised reconstruction for FSE with linear subspace

$$\mathbf{Z}^{(i-1)} = \mathcal{D}_\mathbf{I}\left(\mathbf{X}^{(i-1)}\right) \qquad \mathbf{Z}_\mathbf{I}^{(i-1)} = \mathcal{D}_\mathbf{I}\left(\boldsymbol{\alpha}^{(i-1)}\right)$$

$$\mathbf{X}^{(i)} = \arg\min_{\mathbf{X}} \|\mathbf{Y}_\Theta - \mathbf{M}_\Theta\mathbf{FSX}\|_2^2 + \mu\left\|\mathbf{X} - \mathbf{Z}^{(i-1)}\right\|_2^2 \quad \boldsymbol{\alpha}^{(i)} = \arg\min_{\boldsymbol{\alpha}} \|\mathbf{Y}_{T\Theta} - \mathbf{M}_\Theta\mathbf{FS}\boldsymbol{\Phi}\boldsymbol{\alpha}\|_2^2 + \mu_I\left\|\boldsymbol{\alpha} - \mathbf{Z}_\mathbf{I}^{(i-1)}\right\|_2^2$$

Linear Latent Space defined by SVD

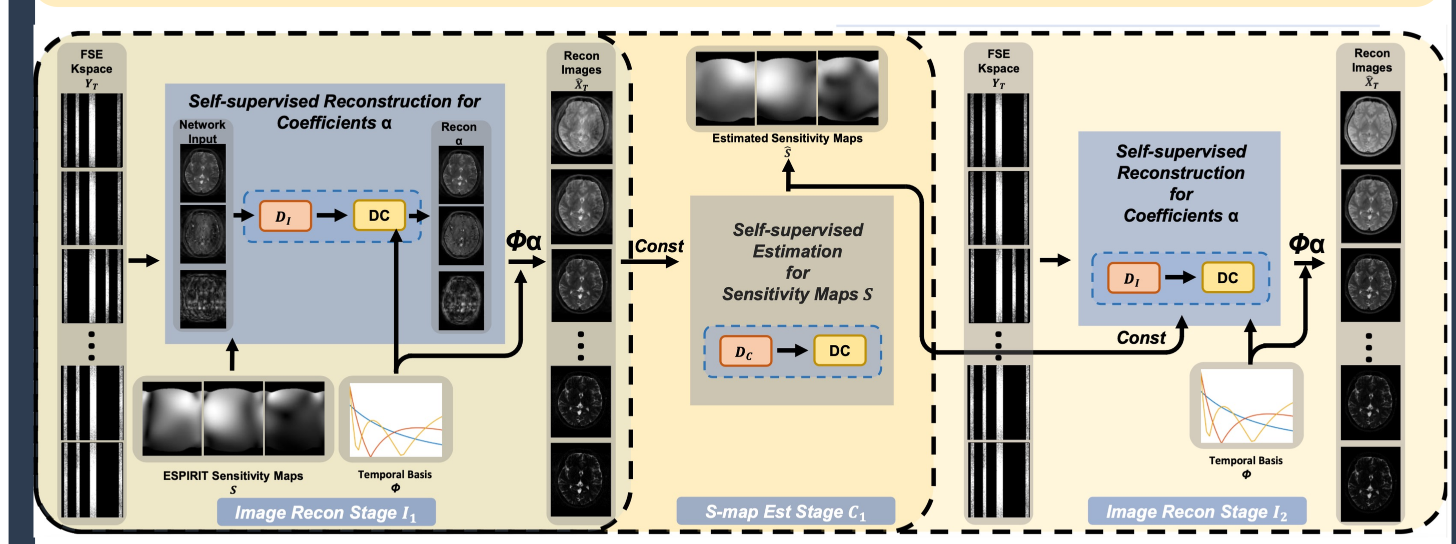
Self-supervised reconstruction for FSE for sensitivity maps estimation

$$\mathbf{Z}_\mathbf{C}^{(i-1)} = \mathcal{D}_\mathbf{C}\left(\mathbf{S}^{(i-1)}\right)$$

$$\mathbf{S}^{(i)} = \arg\min_{\mathbf{S}} \|\mathbf{Y}_{T\Theta} - \mathbf{M}_\Theta\mathbf{FX_TS}\|_2^2 + \mu_C\left\|\mathbf{S} - \mathbf{Z}_\mathbf{C}^{(i-1)}\right\|_2^2 + \lambda_C\|\mathbf{DS}\|_2^2$$

X and S are commutable

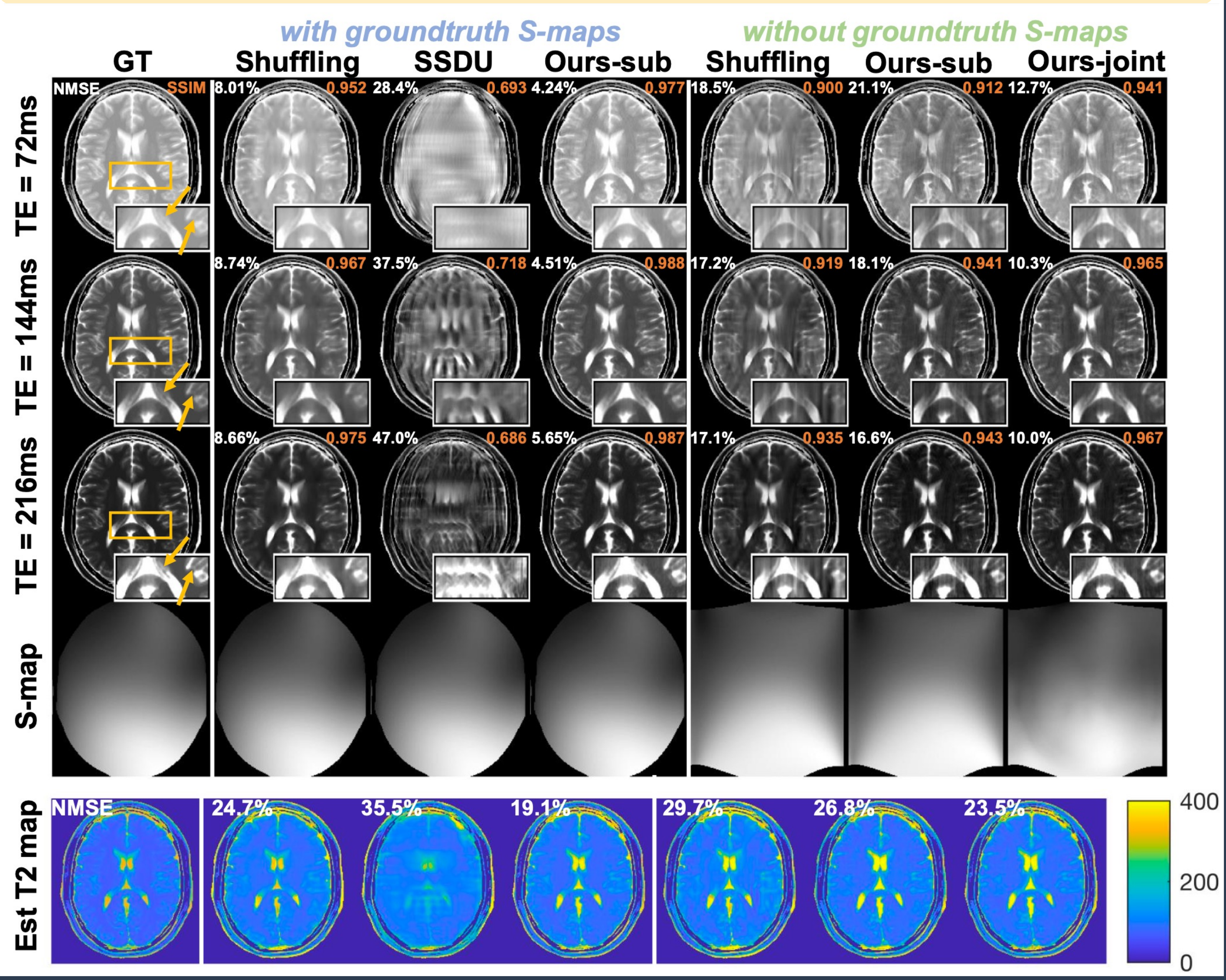
Pipeline for joint reconstructions of FSE images and sensitivity maps



Results

Results for simulated FSE MRI:

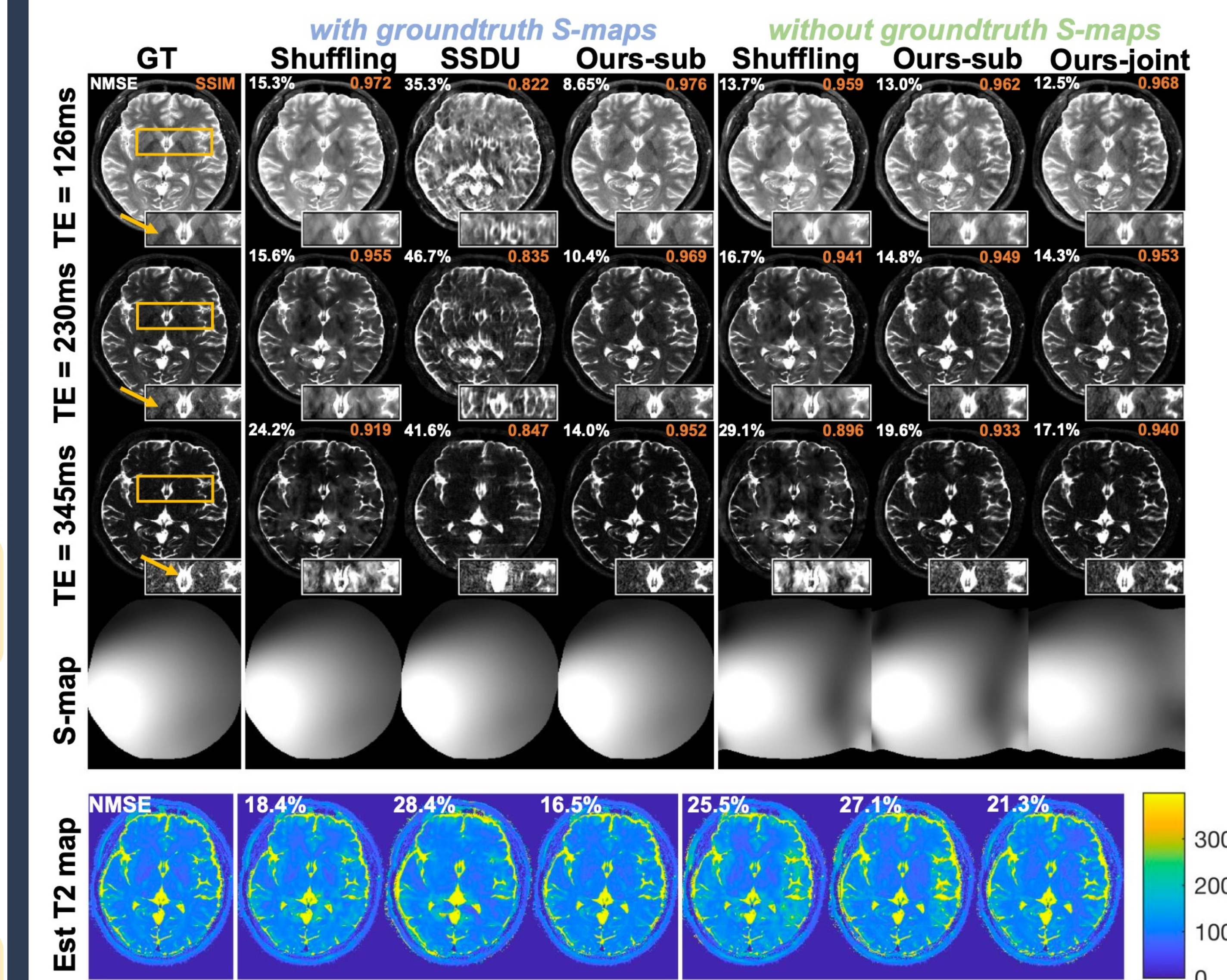
R = 24, 8 coils, T=80 echoes, echo spacing of 5.56ms



Results

Results for realistic FSE MRI:

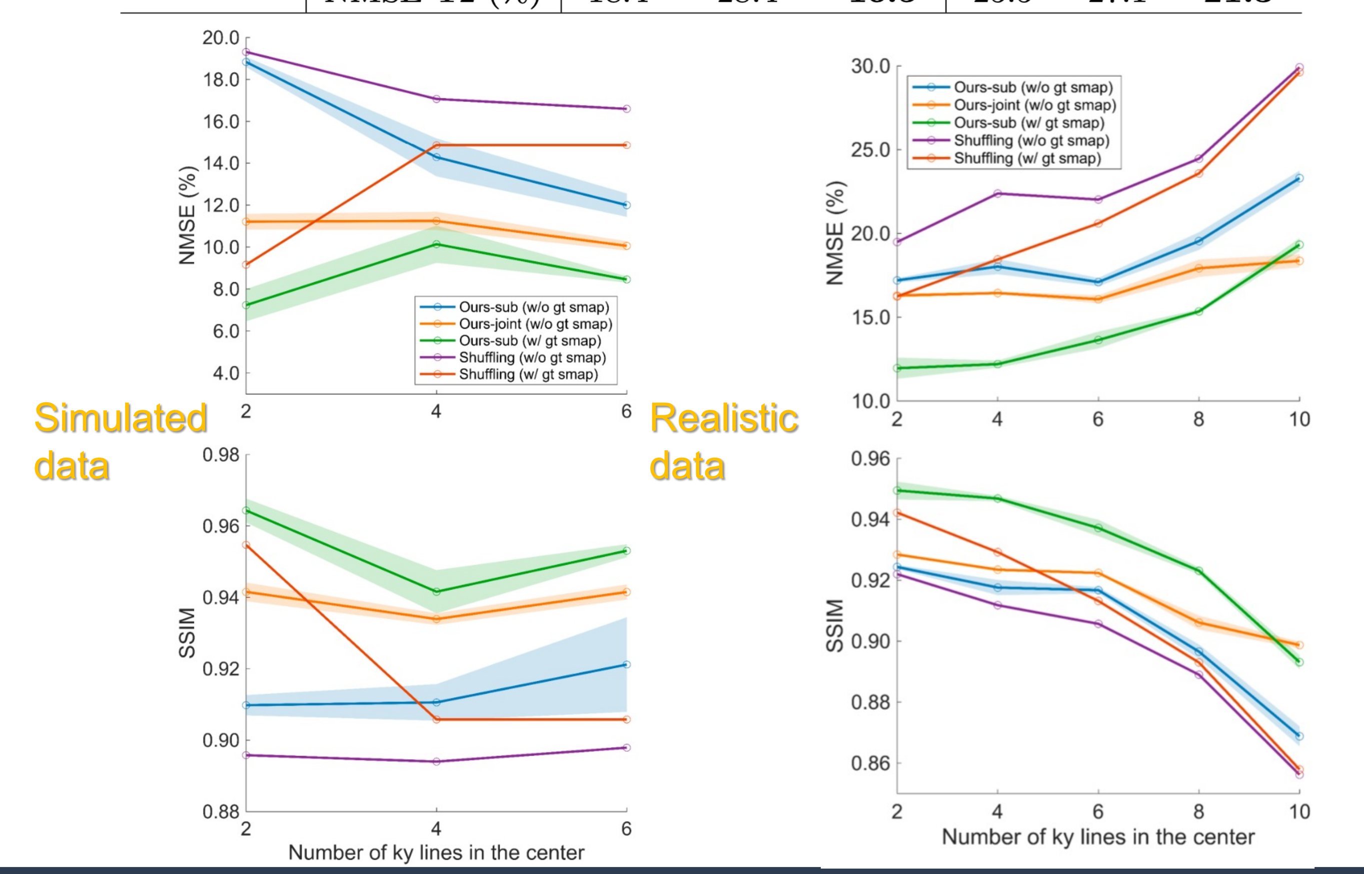
R = 16, 12 coils, T=32 echoes, echo spacing of 11.5ms



Results

Quantities results and ablation studies on # center ky lines

Data	Metric	Sf⋆	SSDU⋆	Sub⋆	Sf	Sub	Joint
Simulated	NMSE-I (%)	9.16	42.3	**7.23**	19.3	18.8	**11.2**
	SSIM-I	0.945	0.693	**0.964**	0.895	0.910	**0.942**
	NMSE-T2 (%)	24.7	35.5	**19.1**	29.7	26.8	**23.5**
In-vivo	NMSE-I (%)	16.2	35.1	**11.9**	19.5	17.2	**16.2**
	SSIM-I	0.942	0.840	**0.950**	0.922	0.924	**0.928**
	NMSE-T2 (%)	18.4	28.4	**16.5**	25.5	27.1	**21.3**



Conclusion

- In this work we proposed a novel zero-shot self-supervised reconstruction framework on a linear latent space to simultaneously learn a regularizer from the highly under-sampled data itself and exploit temporal correlations to significantly reduce degrees of freedom in the reconstruction.
- Moreover, a self-supervised sensitivity estimation stage is proposed which only utilizes the acquired data to further shorten the total scanning time.

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