Deep subspace learning for efficient reconstruction of spatiotemporal imaging data

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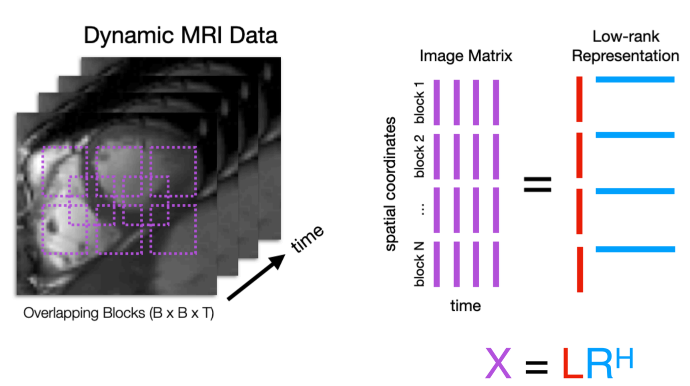
Motivation

Model-based deep learning approaches, such as unrolled neural networks[1] have demonstrated state-of-the-art performance for efficiently solving inverse problems[2-4]. However, the memory costs of training unrolled neural networks remains high, especially when the target data is high-dimensional. This often requires trade-offs in network depth to reduce model size, or spatiotemporal resolution to reduce data size.

To this end, we propose **DL-Subspace**: a novel unrolled neural network architecture which reduces memory usage by solving for low-dimensional, compact representations of spatiotemporal imaging data. DL-Subspace is applied to reconstruction of accelerated dynamic magnetic resonance imaging (MRI) data, demonstrating up to **4X higher memory efficiency** and **4X faster inference speeds** while maintaining similar image quality metrics as state-of-the-art unrolled networks.

Methods

- Subspace Model[5]: Dynamic MRI data can be represented as a product of two matrices containing spatial and temporal basis functions (L, R)
- If the data is sufficiently low-rank, then the data can be represented compactly using few basis functions



- Inspired by Arvinte et al.[6], the compact, low-rank representation can be solved for directly using a model-based alternating minimization algorithm:

Bi-linear Regularized Least Squares Objective:

$$\underset{L,R}{\text{minimize}}\ ||Y - \mathscr{A}(LR^H)||_F^2 + ||\Psi(L) - L||_F^2 + ||\Phi(R) - R||_F^2$$

DL-Subspace Update Rule:

$$\begin{cases} U^{(i+1)} = \underset{L}{\arg\min}\ ||Y - \mathscr{A}(LR^{(i)H})||_F^2 + \mu_l ||L^{(i)} - L||_F^2 \\ L^{(i+1)} = \Phi(U^{(i+1)}) \\ V^{(i+1)} = \underset{R}{\arg\min}\ ||Y - \mathscr{A}(L^{(i+1)}R^H)||_F^2 + \mu_r ||R^{(i)} - R||_F^2 \\ R^{(i+1)} = \Psi(V^{(i+1)}) \end{cases}$$

- Basis denoisers (Ψ, Φ) are parameterized by 2-D and 1-D CNNs respectively, and learned by unrolling the update rule above to form the DL-Subspace network architecture:

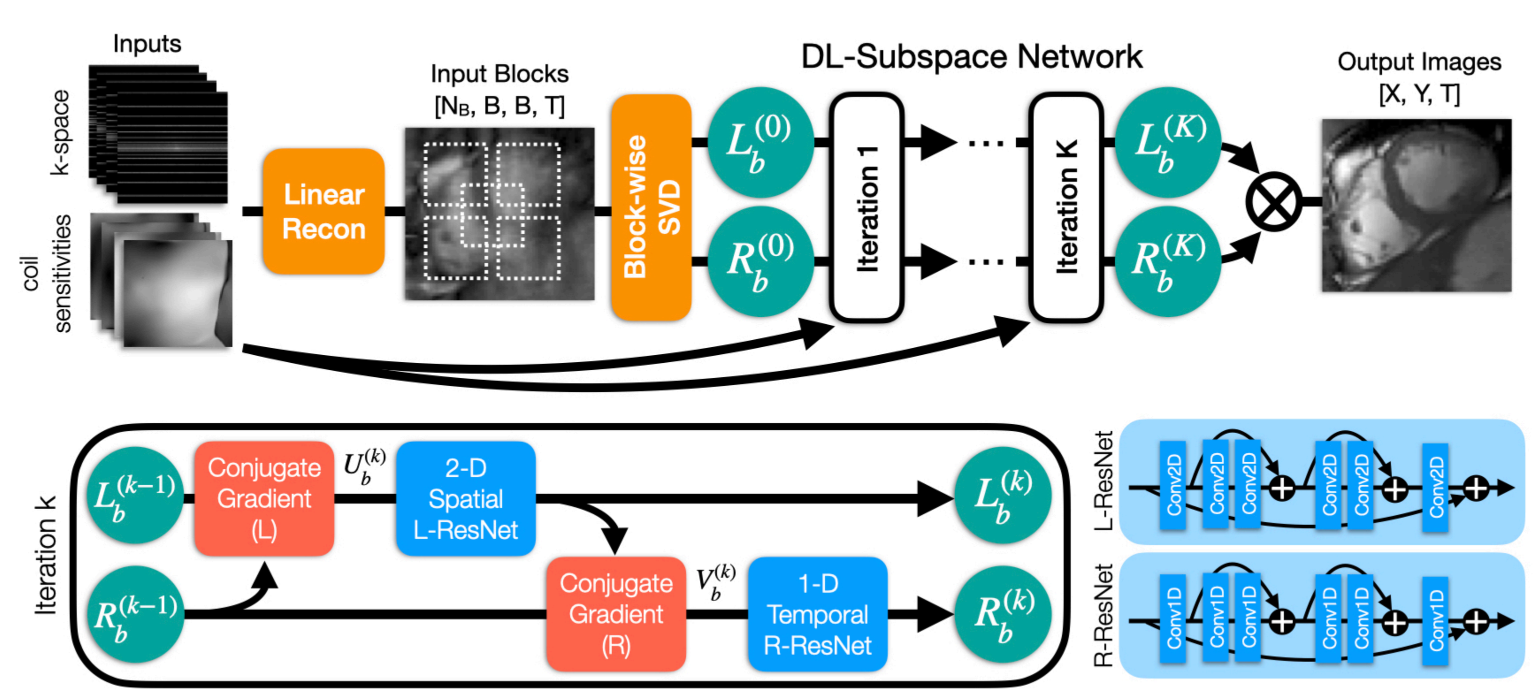


Fig. 1: DL-Subspace Network Architecture: Combines model-based unrolled networks with a subspace model to achieve memory efficient training and inference.

	# Unrolls	# CG Unrolls	# Learnable Parameters	Sub-Network Architecture	Kernel Size	# Input Features	# Hidden Features
DL-ESPIRiT	10	N/A	8.5 million	2D+Time ResNet-5	3 x 3 x 3	2	88
MoDL	10	10	8.5 million	2D+Time ResNet-5	3 x 3 x 3	2	88
DL-Subspace	10	10	8.6 million	2D ResNet-5	3 x 3	24	128
				1D ResNet-5	3 x 1	24	128

- DL-Subspace is compared against MoDL[3] and DL-ESPIRiT[4] unrolled networks
- All three networks are trained using a supervised L1 loss on multi-slice cardiac MRI data acquired from 21 healthy volunteers (17/3/1 split) + 1 pediatric patient for testing

Results

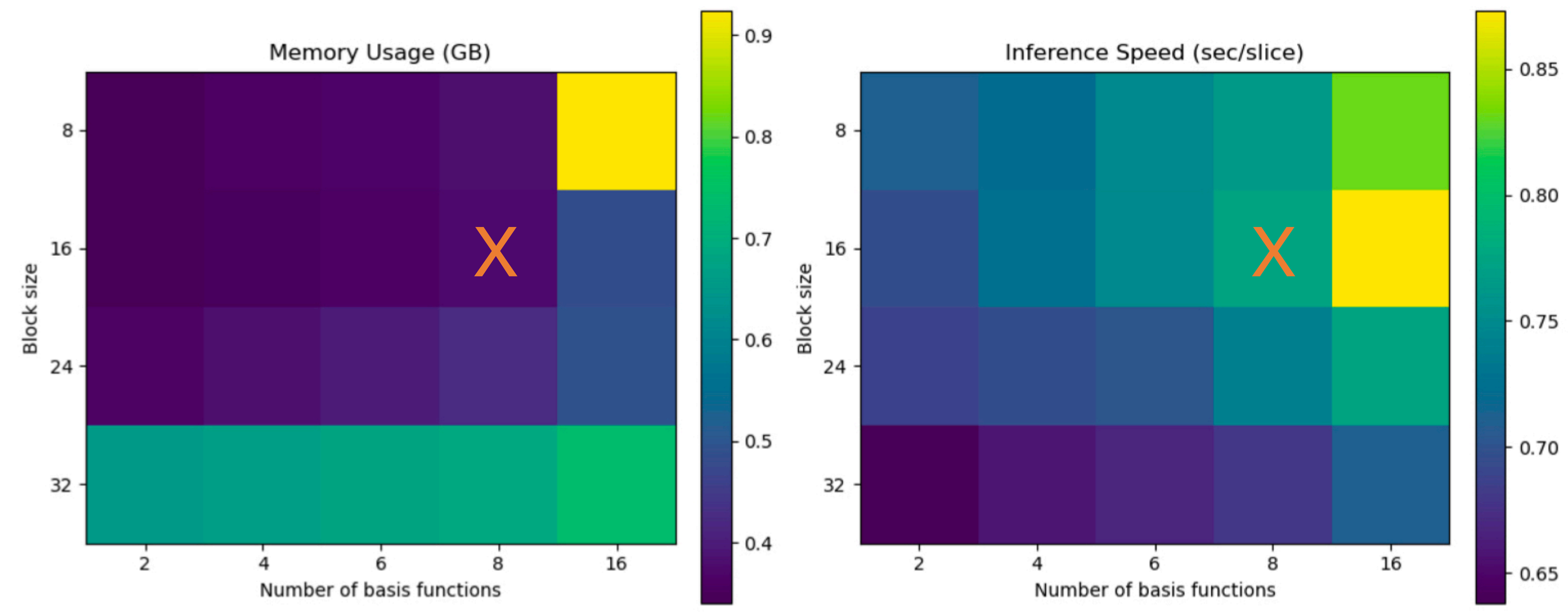


Fig. 2: Memory usage (GB) and inference speed (sec/slice) for DL-Subspace with varying block size and number of basis functions. For reference, memory usage of DL-ESPIRiT and MoDL is 1.6 GB. Average inference speed for DL-ESPIRiT and MoDL are 2.5 and 2.8 sec/slice respectively

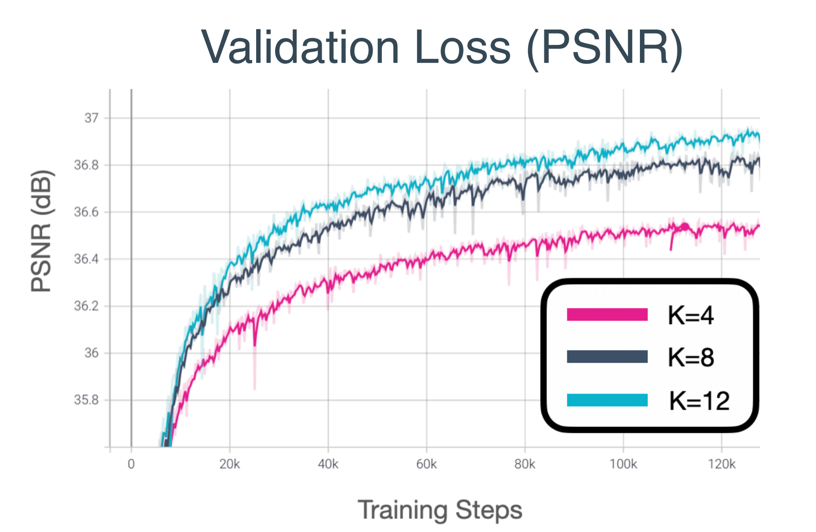


Fig. 3: Effect of number of basis functions (K) on image reconstruction quality in validation set

- DL-Subspace shows higher memory efficiency and faster inference speeds compared to DL-ESPIRiT and MoDL across a wide range of hyperparameters
- Reconstruction quality is greatly impacted by choice of K
- A balance between reconstruction quality and memory efficiency is achieved by choosing K=8, but note that the optimal K will vary based on dataset and task

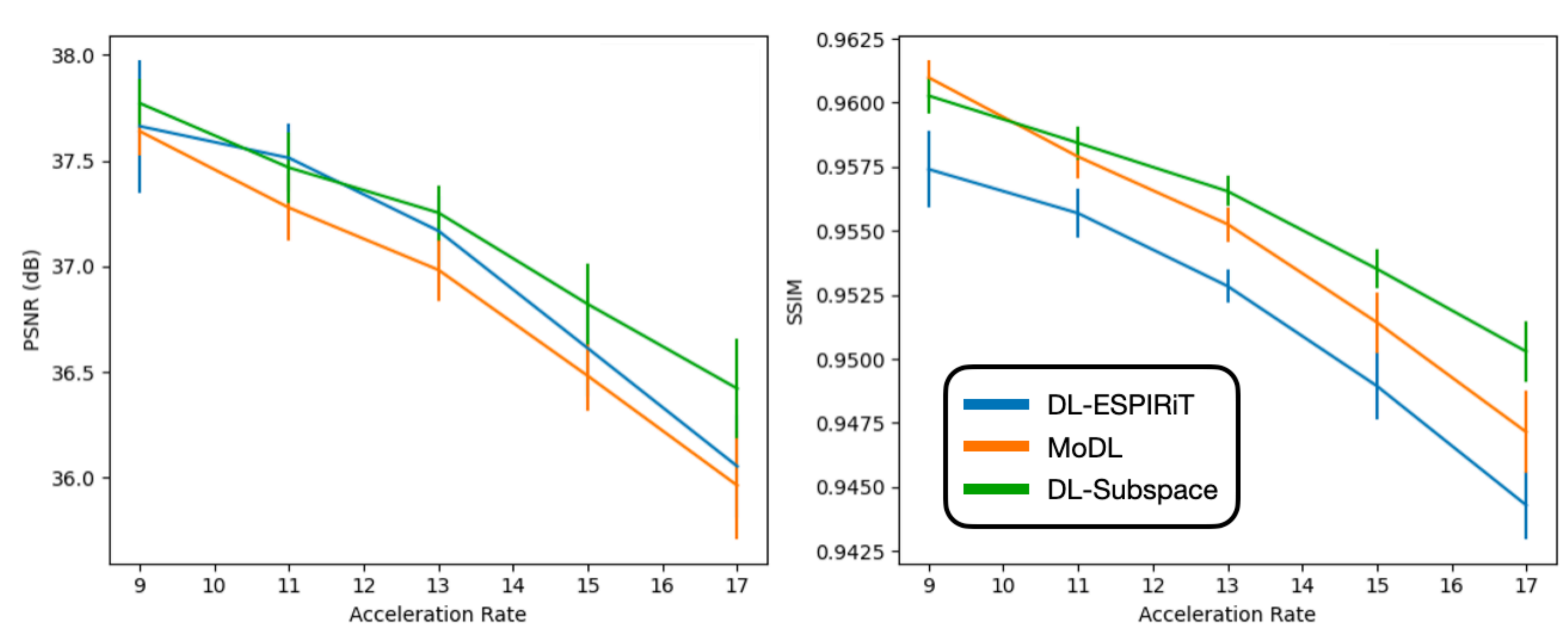


Fig. 4: Reconstruction quality evaluated with respect to PSNR and SSIM for all three networks across a range of simulated scan time acceleration rates.

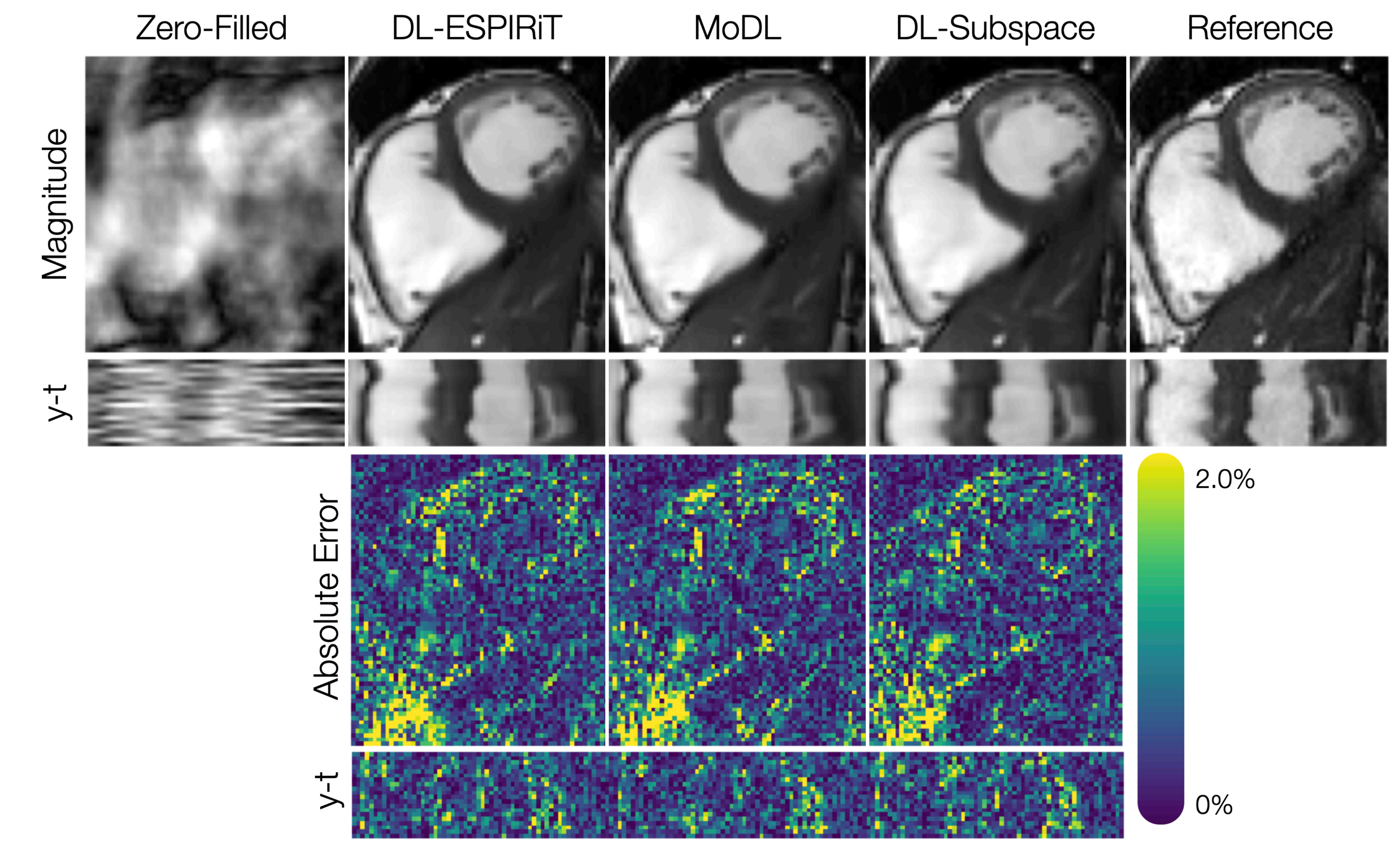


Fig. 5: Reconstructions of a retrospectively accelerated dataset from healthy volunteer. No significant difference is observed between DL-ESPIRiT, MoDL, and DL-Subspace images.

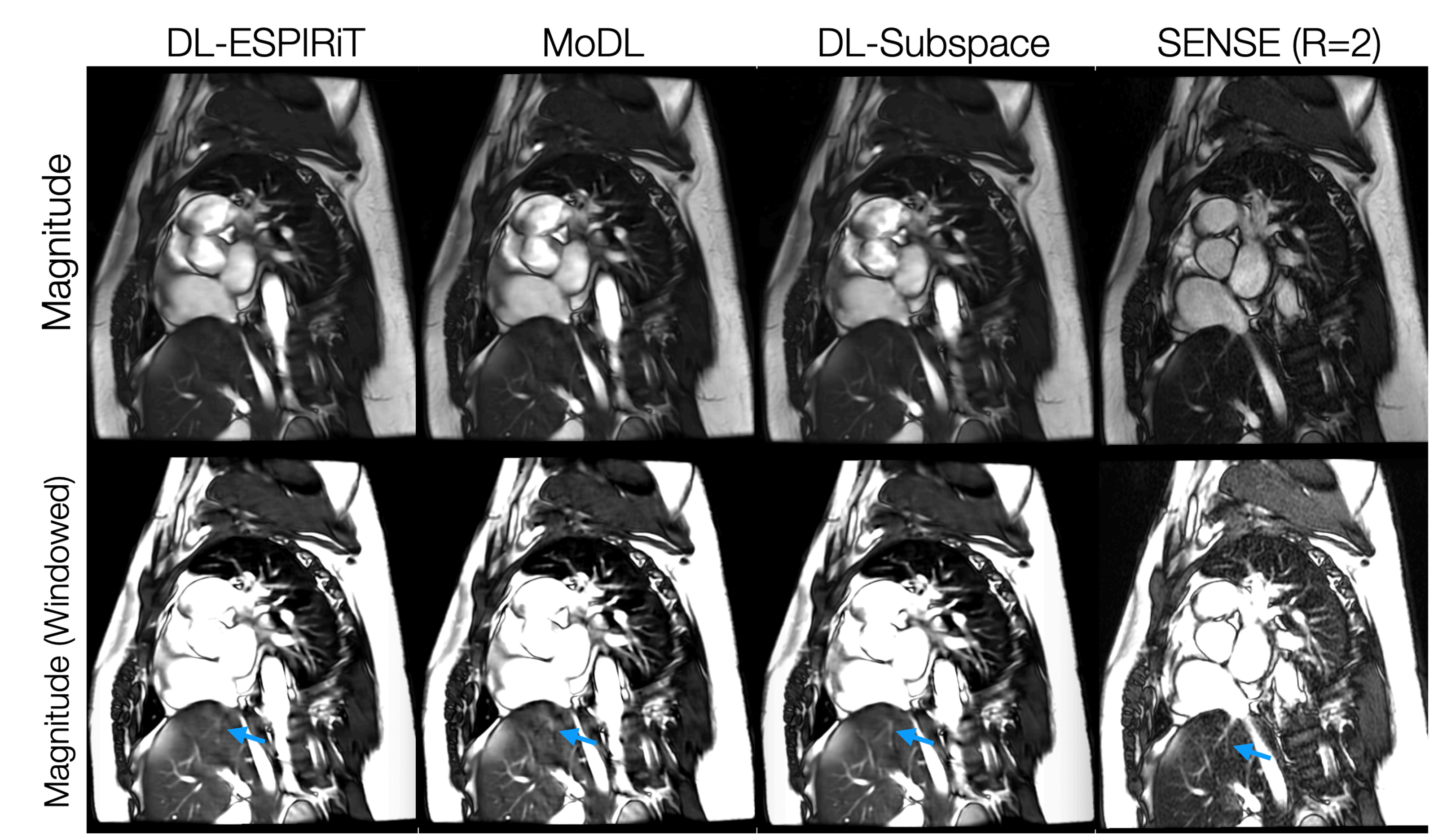


Fig. 6: Reconstructions of a prospectively accelerated dataset from pediatric patient. DL-Subspace reconstruction depicts slightly better image quality due to enhanced denoising imposed by low-rank prior (blue arrow).

Conclusion

A novel DL-Subspace reconstruction framework is proposed, which uses a subspace model to curb memory requirements of training unrolled neural networks for spatiotemporal image reconstruction. Further validation is necessary to determine efficacy across a larger patient cohort

References

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