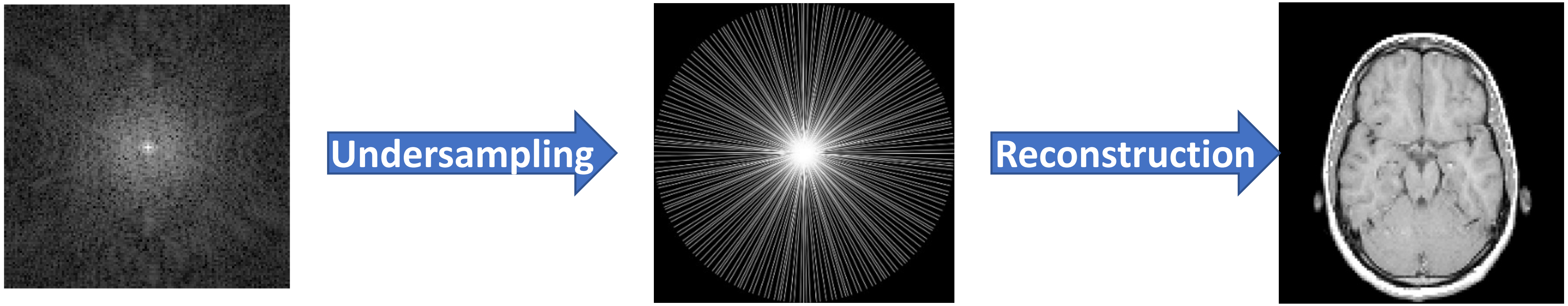
Fast magnetic resonance imaging using adaptive convolutional neural networks for *k*-space data interpolation

Yong Fan
Department of Radiology
Perelman School of Medicine
University of Pennsylvania

Fast MRI with sparse *k*-space sampling



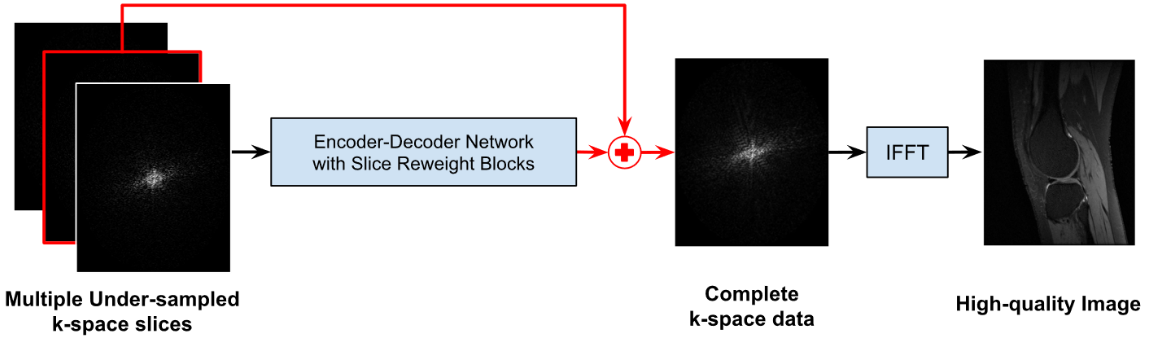
Full *k*-space data **Sparse *k*-space data** **Reconstructed image**

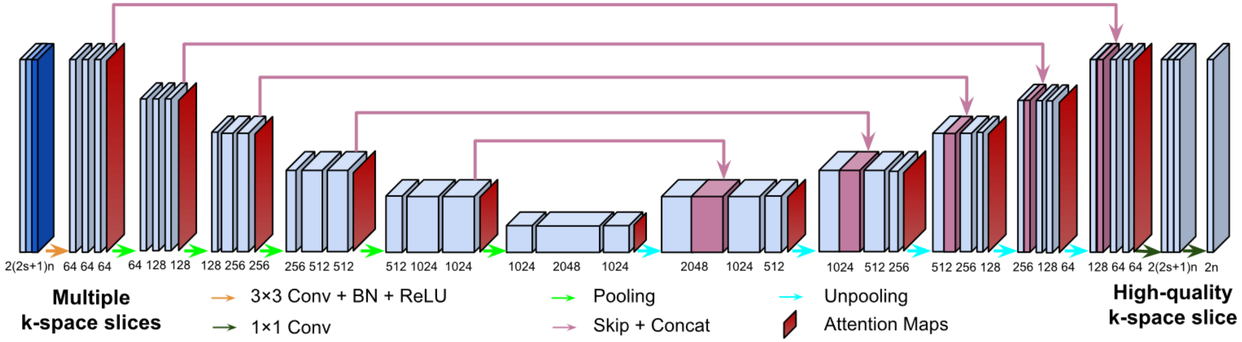
Data interpolation methods for image reconstruction from sparse *k*-space data

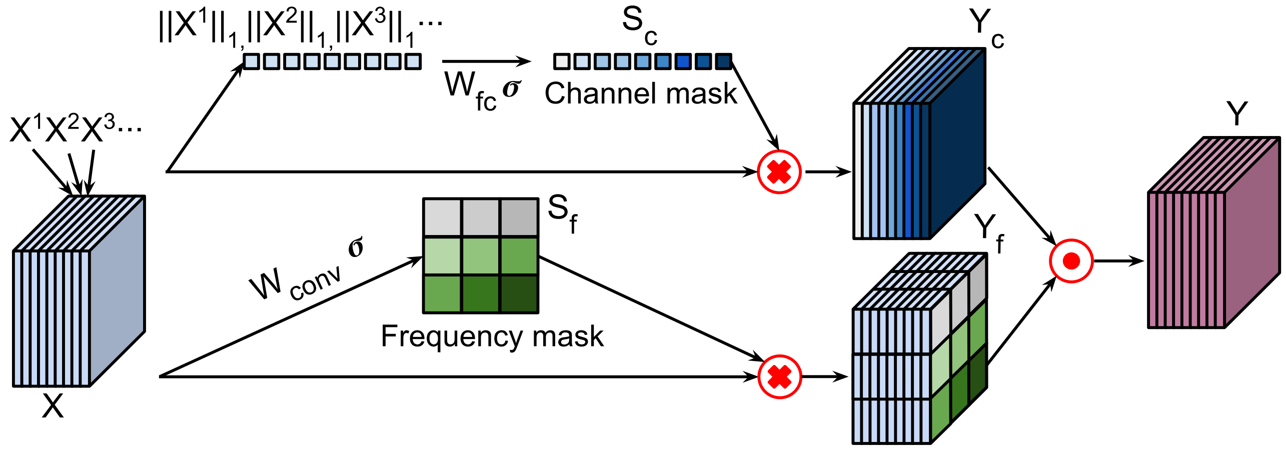
- **Compressed sensing methods**
- **Deep learning methods: convolutional neural networks (CNNs)**
  - Interpolation in image domain
  - Interpolation in k-space domain
  - Interpolation in both domains

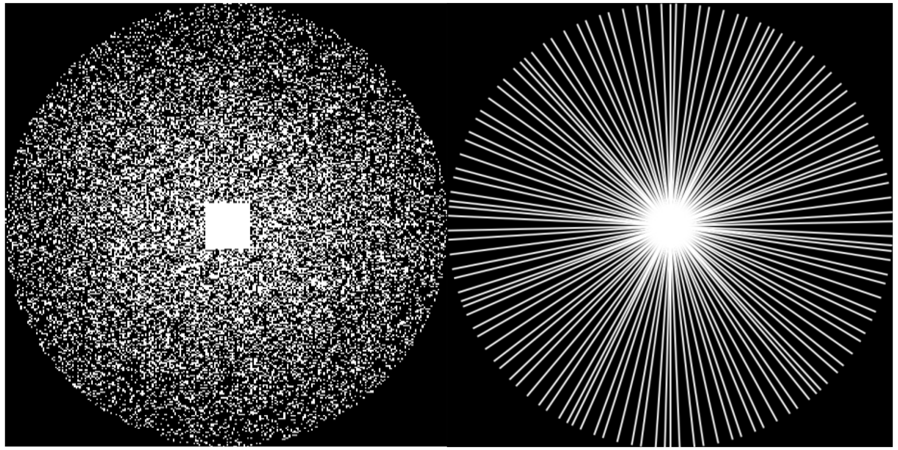
CNNs with shared weights are applied to low- and high- frequency data that contribute differently to the image reconstruction !

Adaptive CNNs for *k*-space data interpolation







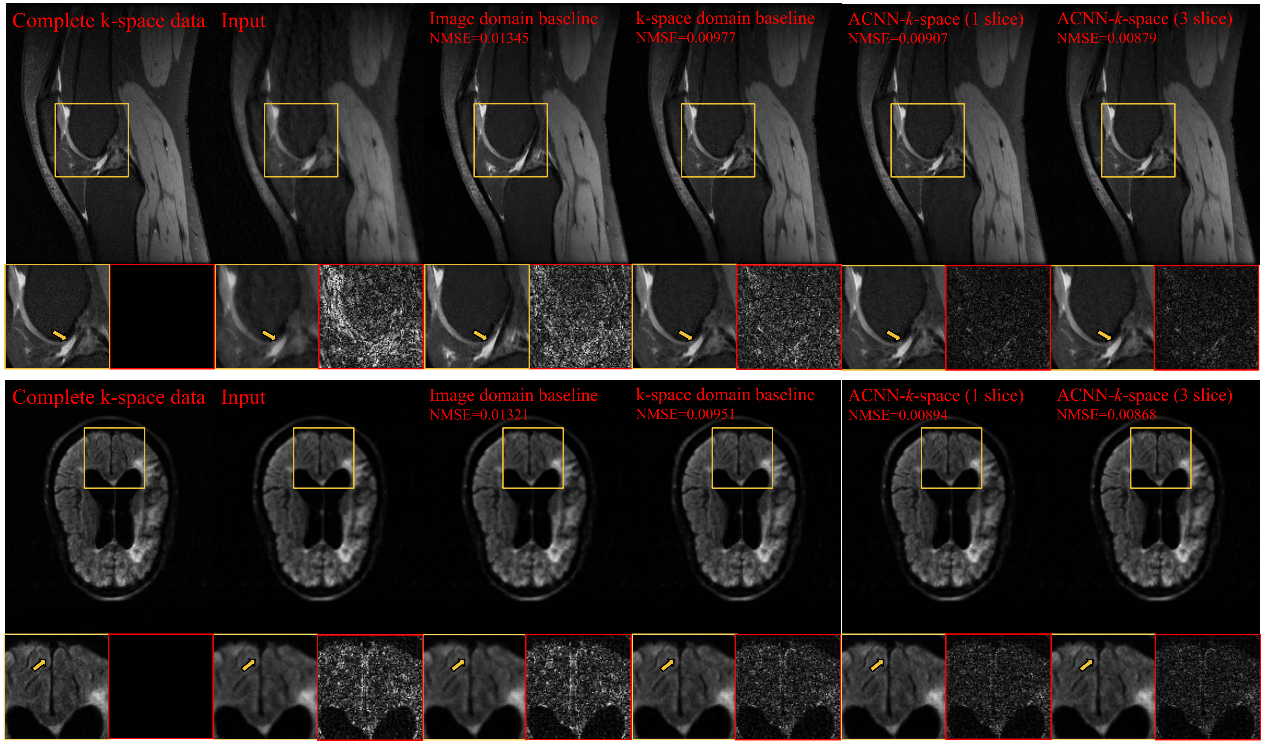


Sampling masks. Left: Cartesian trajectory. Right: Radial trajectory

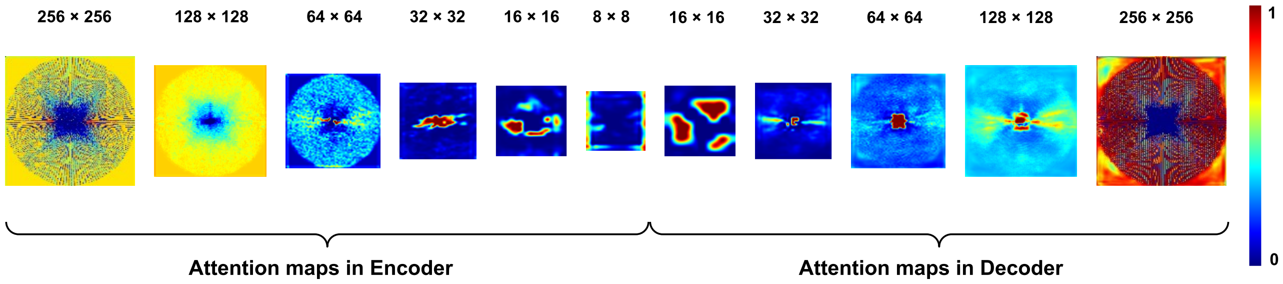
- **We evaluated our method using two publicly available datasets, including Stanford Fully Sampled 3D FSE Knee *k*-space Dataset (available at http://mridata.org/), and fastMRI Brain Dataset (available at https://fastmri.org).**

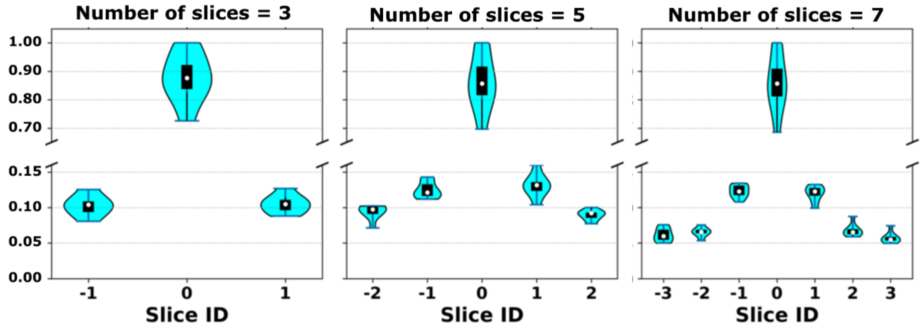
- **We compared our method with a recently published *k*-space deep learning method, as well as an image domain deep learning method. Both of these methods were built upon the same U-net architecture.**

Performance evaluation based on *k*-space datasets



Frequency-attention maps learned for k-space data undersampled using Radial sampling.





Channels contributed differently to the image reconstruction.

PERFORMANCE OF METHODS UNDER COMPARISON BASED ON THE FASTMRI BRAIN DATASET.

Methods	Number of input slices	NMSE (× 10^{-3})				PSNR				SSIM (× 10^{-2})			
		Cartesian		Radial		Cartesian		Radial		Cartesian		Radial	
		mean±std	p-value	mean±std	p-value	mean±std	p-value	mean±std	p-value	mean±std	p-value	mean±std	p-value
Image-domain	1	20.43±0.02	1.81e-3	16.16±0.02	2.25e-3	38.25±3.23	6.05e-4	39.74±3.19	7.95e-7	94.11±0.05	1.27e-5	94.46±0.05	6.05e-4
k-space	1	19.67±0.02	3.34e-2	15.71±0.02	3.62e-6	38.60±2.97	3.39e-4	39.85±3.26	7.49e-3	94.58±0.05	5.27e-6	94.61±0.05	4.81e-9
ACNN-k-Space	1	18.80±0.02	2.32e-3	15.29±0.02	2.61e-2	38.95±3.20	2.57e-3	40.11±3.27	5.05e-e2	94.62±0.05	8.96e-5	94.86±0.05	5.57e-3
	3	**18.30**±0.02	-	**14.93**±0.02	-	**39.16**±3.03	-	**40.39**±3.30	-	**95.02**±0.05	-	**95.21**±0.05	-

Discussion and Conclusions

- **Our residual Encoder-Decoder network of CNNs can integrate complementary information of spatially adjacent slices to improve image reconstruction.**
- **Self-attention layers can effectively integrate complementary information of multiple slices and recognize distinctive contributions of k-space data at different spatial frequencies.**
- **Ablation studies and comparison experiments have demonstrated that our method could effectively reconstruct images from undersampled k-space data and achieved significantly better image reconstruction performance than state-of-the-art alternative techniques.**
- **Our network is built upon the standard residual Encoder-Decoder network architecture, which could be improved by adopting other network architectures, network blocks, and advanced learning strategies.**
- **Our method can serve as a basic deep learning component to be integrated with other deep learning methods in a straightforward manner.**