Parallel qMRI Reconstruction from 4x Accelerated Acquisitions

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INTRODUCTION

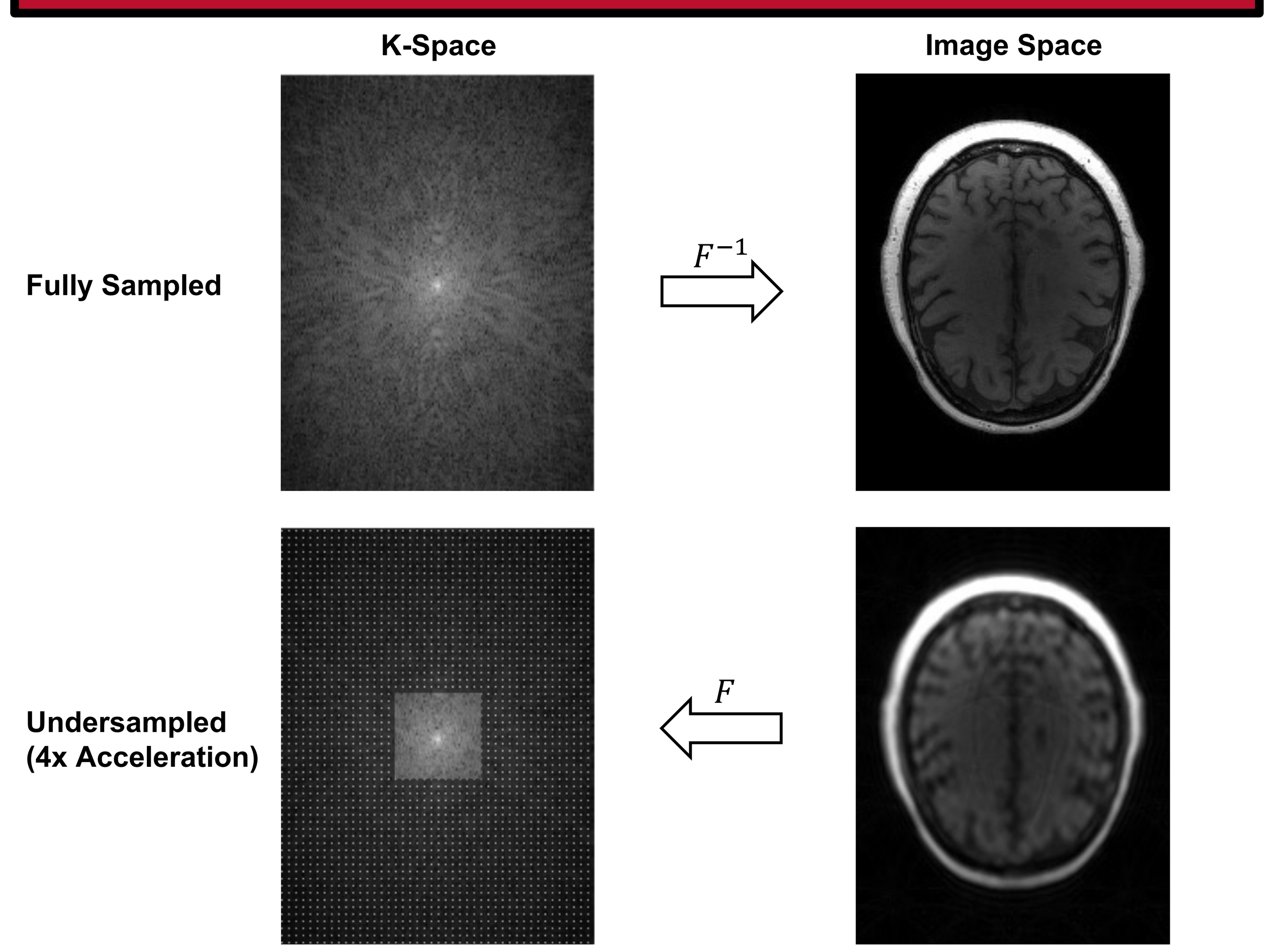
- Full MRI acquisitions require extensive scan times, limiting patient throughput and increasing motion artifacts.
- Accelerated parallel MRI reduces acquisition time by under sampling k-space data (e.g., measuring every 4th line in 4x acceleration).
- Traditional reconstruction methods like SENSE require both undersampled k-space data and pre-computed coil sensitivity maps.
- We propose a deep learning framework that jointly estimates coil sensitivity maps and reconstructs images from only undersampled measurements.

DATA OVERVIEW

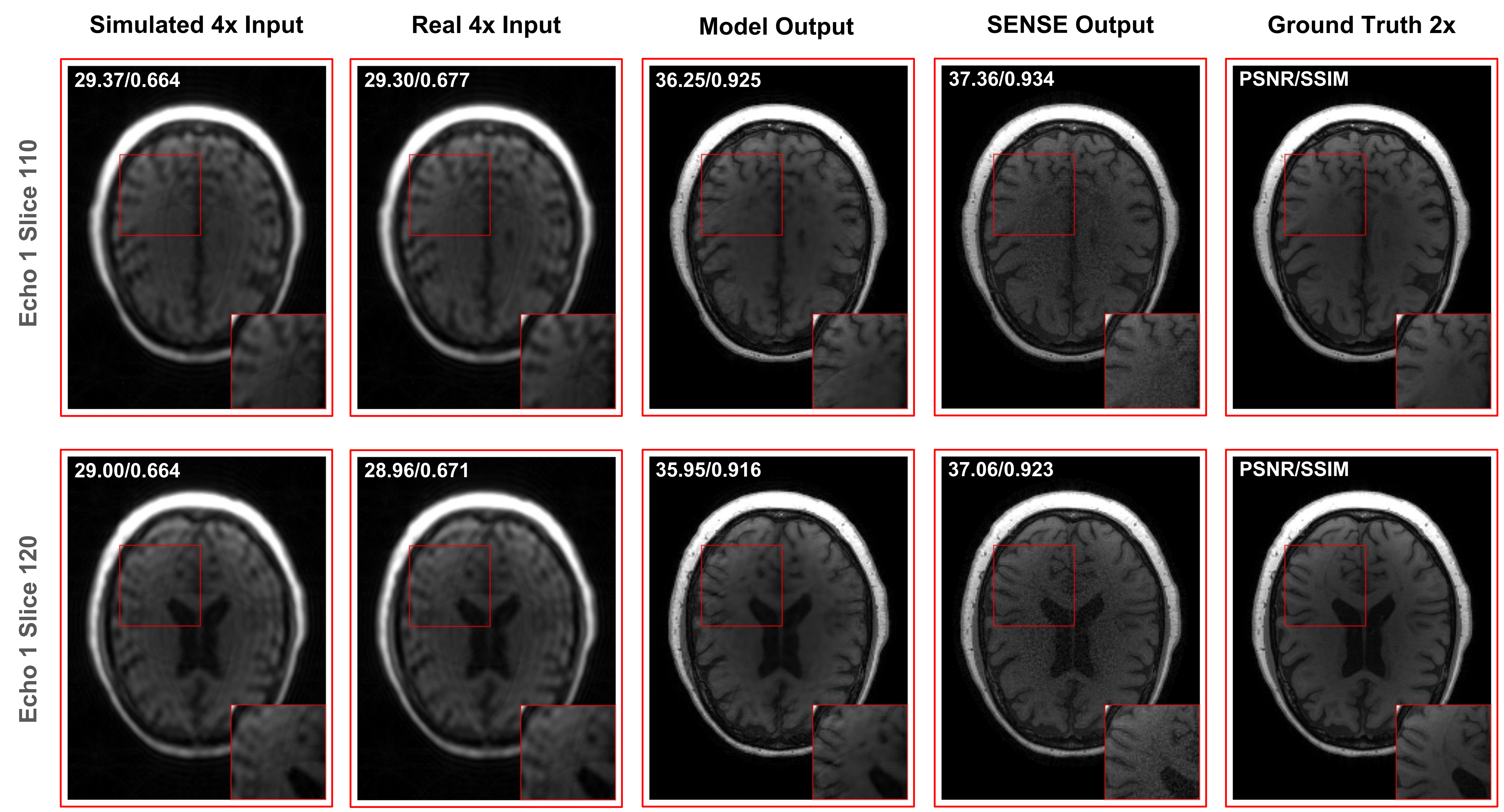
Measurements	Count	Shape [Coils, H, W]
Subjects	10	-
Echoes	8	-
Coils	64	-
Slices	70	-
K-Space 2x (total)	5,600	[64, 234, 176]
K-Space 4x (total)	5,600	[64, 234, 176]
Sensitivity Maps (total)	5,600	[64, 234, 176]

Note: MRI measurements provided by Washington University Medical School.

ACCELERATED ACQUISITION

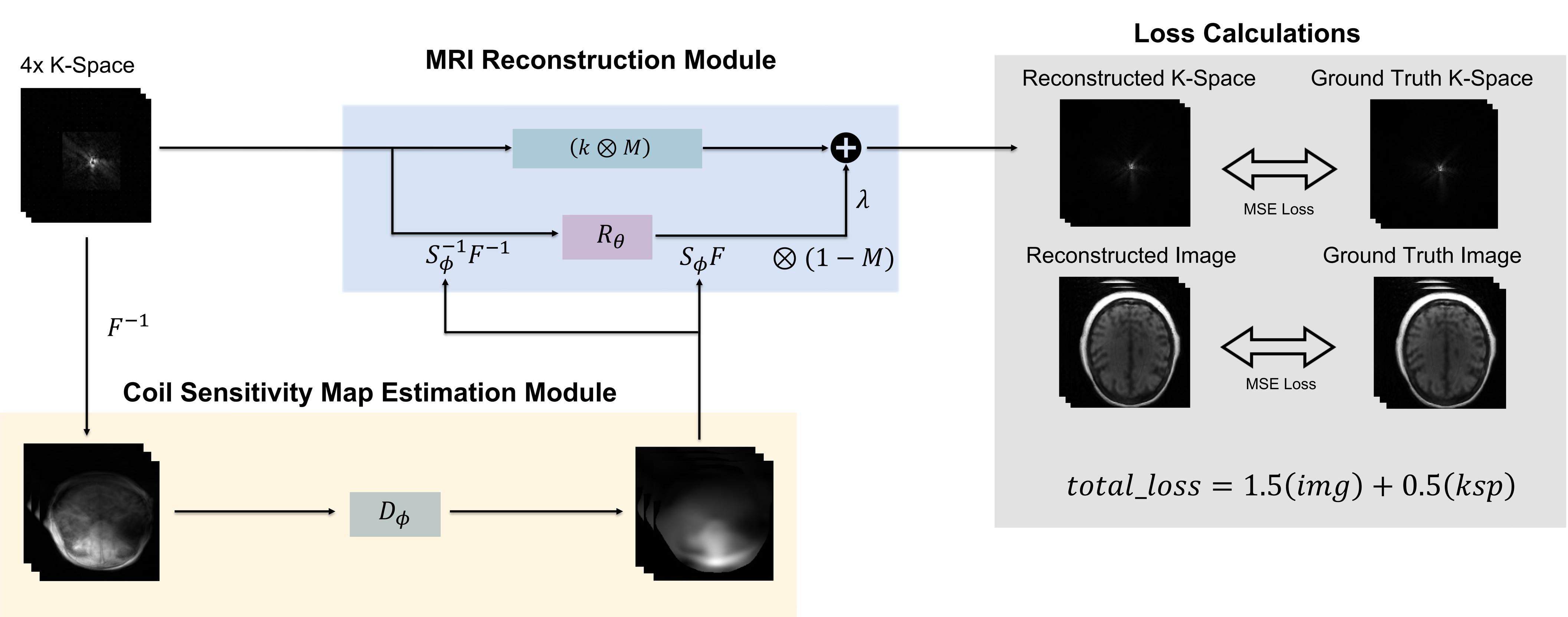


RESULTS



Note: Measurements from Subject S012, 1st Echo, Slices 110 and 120. Normalized for visual output.

MODEL ARCHITECTURE



$$k^+ = (k \otimes M) + \lambda((1-M) \otimes FS_\phi R_\theta(S_\phi^{-1}F^{-1}k))$$
$$k^+ = (k \otimes M) + \lambda((1-M) \otimes k')$$

DISCUSSIONS

- Our method produces smoother reconstruction compared to speckled SENSE output, achieving comparable visual quality despite lower PSNR/SSIM scores.
- Training on simulated 4x data (masked 2x acquisitions) yields superior reconstruction quality compared to real 4x accelerated data.
- The two-module design enables independent optimization of Coil Sensitivity Map estimation and image reconstruction components.
- Spatial misalignment, k-space shifts, and intensity distribution differences between acceleration factors degraded performance, requiring careful normalization for fair comparison.
- Future work will implement deep unfolding and plug-and-play architectures to improve reconstruction quality.
- Next steps include aligning real 4x acquisitions with 2x ground truth and exploring larger parameter models.

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