Learning to Sample MRI via Variational Information Maximization

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Summary

We present a framework for **learning the sampling pattern** in MRI jointly with reconstruction using **variational information maximization**. Experiments with knee MRI shows improved reconstruction quality of our data-driven sampling over the prevailing variable-density sampling.

Background

- MRI measures tissue properties by collecting spatial Fourier domain representations (k-space).
- One of the **main challenges** in MRI is the **long scan times**.
- In order to **accelerate MR imaging**, one can obtain a **reduced number of k-space samples** below the Nyquist rate and use compressed sensing or deep learning methods to solve the inverse problem.

Problem Statement

- Accelerating MRI scans requires **optimal sampling** of k-space data. However the sampling trajectories are usually selected heuristically.
- Can we optimize for the sampling locations in k-space in a data-driven manner?
- Given an acceleration factor, is it possible to optimize sampling pattern and image reconstruction jointly?

Our solution: We put forth a novel deep learning framework that leverages **uncertainty autoencoders** to enable joint optimization of sampling pattern and reconstruction of MRI scans.

Methods

We consider the multi-coil MR signal model under the additive white complex Gaussian noise as

$$z = f_\phi(x) + \epsilon = \left[(F_{nu}(\phi)S_1)^H \cdots (F_{nu}(\phi)S_C)^H\right]^H x + \epsilon$$

where x is the image, z is k-space measurements. Encoding model $f_\phi(x)$ contains coil sensitivity information S_i, and enables continuous parameterization of sampling coordinates ϕ via nuFFT operator $F_{nu}(\phi)$.

Variational Information Maximization

We make use of the InfoMax principle that maximizes the mutual information between the measurements and noisy latent representations

$$\begin{aligned}\max_\phi I_\phi(X,Z) &= \max_\phi \mathbb{E}_{q_\phi(X,Z)}[\log q_\phi(X|Z)] \\ &\geq \max_{\phi,\theta} \mathbb{E}_{q_\phi(X,Z)}[\log p_\theta(X|Z)]\end{aligned}$$

where $p_\theta(X|Z)$ is a variational approximation to the model posterior $q_\phi(X|Z)$. We represent the loss function as

$$\mathcal{L}(\phi,\theta;\mathcal{D}) = \max_{\phi,\theta} \sum_{x\in\mathcal{D}} \mathbb{E}_{q_\phi(Z|x)}[\log p_\theta(x|z)]$$

Network Architecture

We use the nuFFT operator for multi-coil encoding and unrolled network architecture for decoding. Sampling locations ϕ are shared between encoder and decoder.

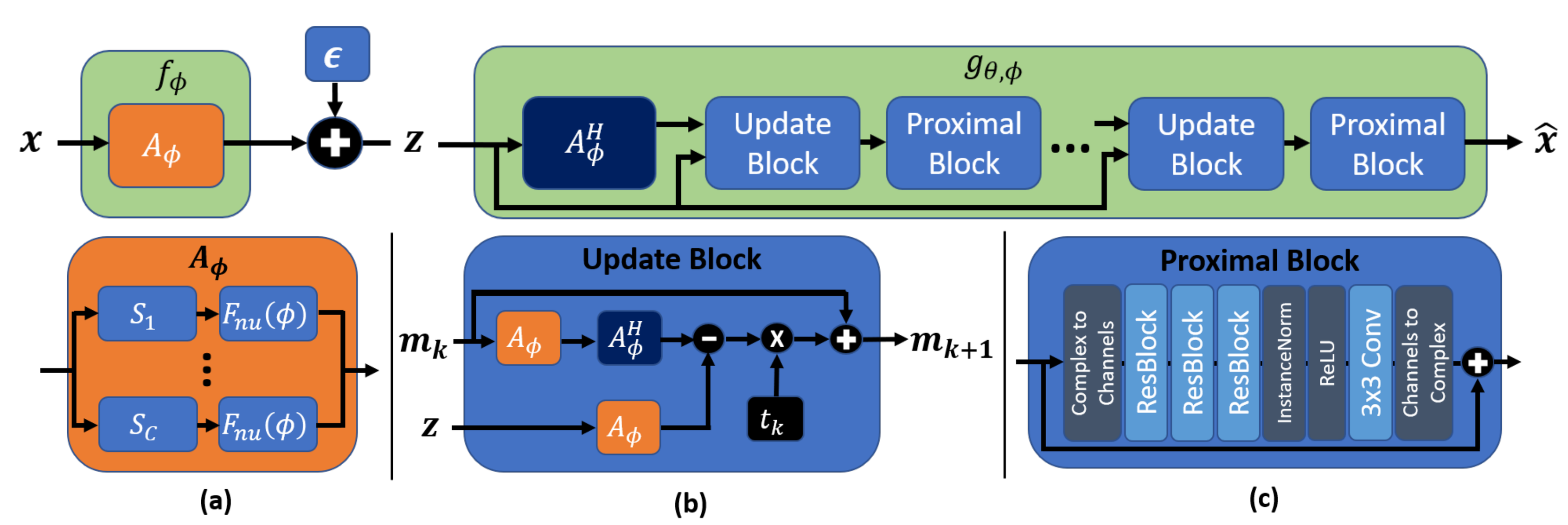

Figure 1: Network architecture consisting of nuFFT based encoder (a) and unrolled reconstruction network (b, c).

Experiments

We considered four acceleration factors in our experiments: $R = 5, 10, 15, 20$. For each acceleration factor, we initialized the k-space sampling pattern (ϕ) by Variable Density Sampling and picked $\sigma = 0.001$ for the measurement noise ϵ.

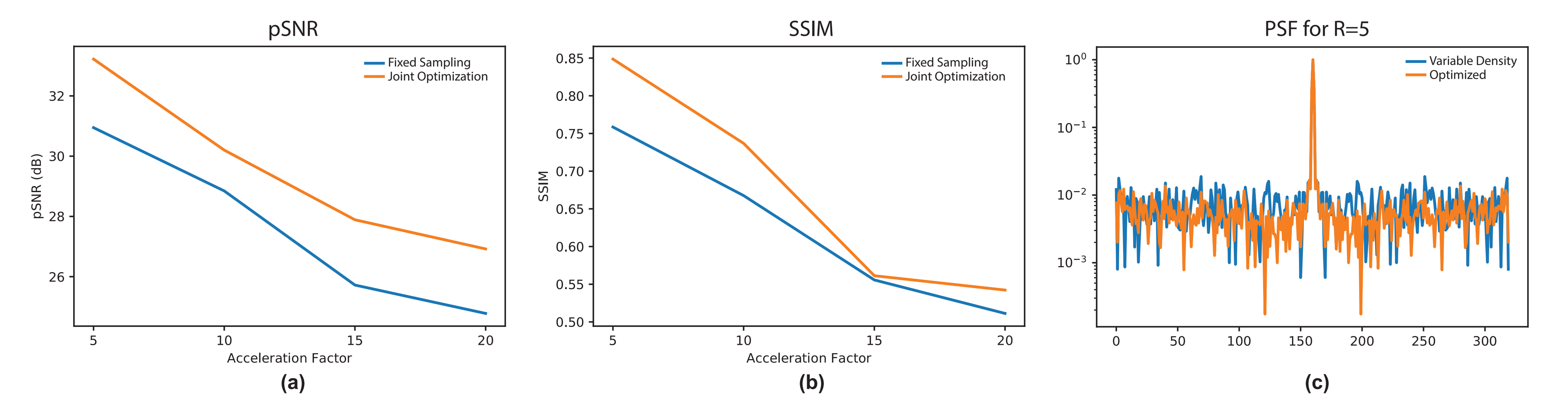

Figure 2: pSNR (a) and SSIM (b) evaluated on test set for different acceleration factors. Point spread function (c) of sampling trajectories before and after optimization for $R = 5$.

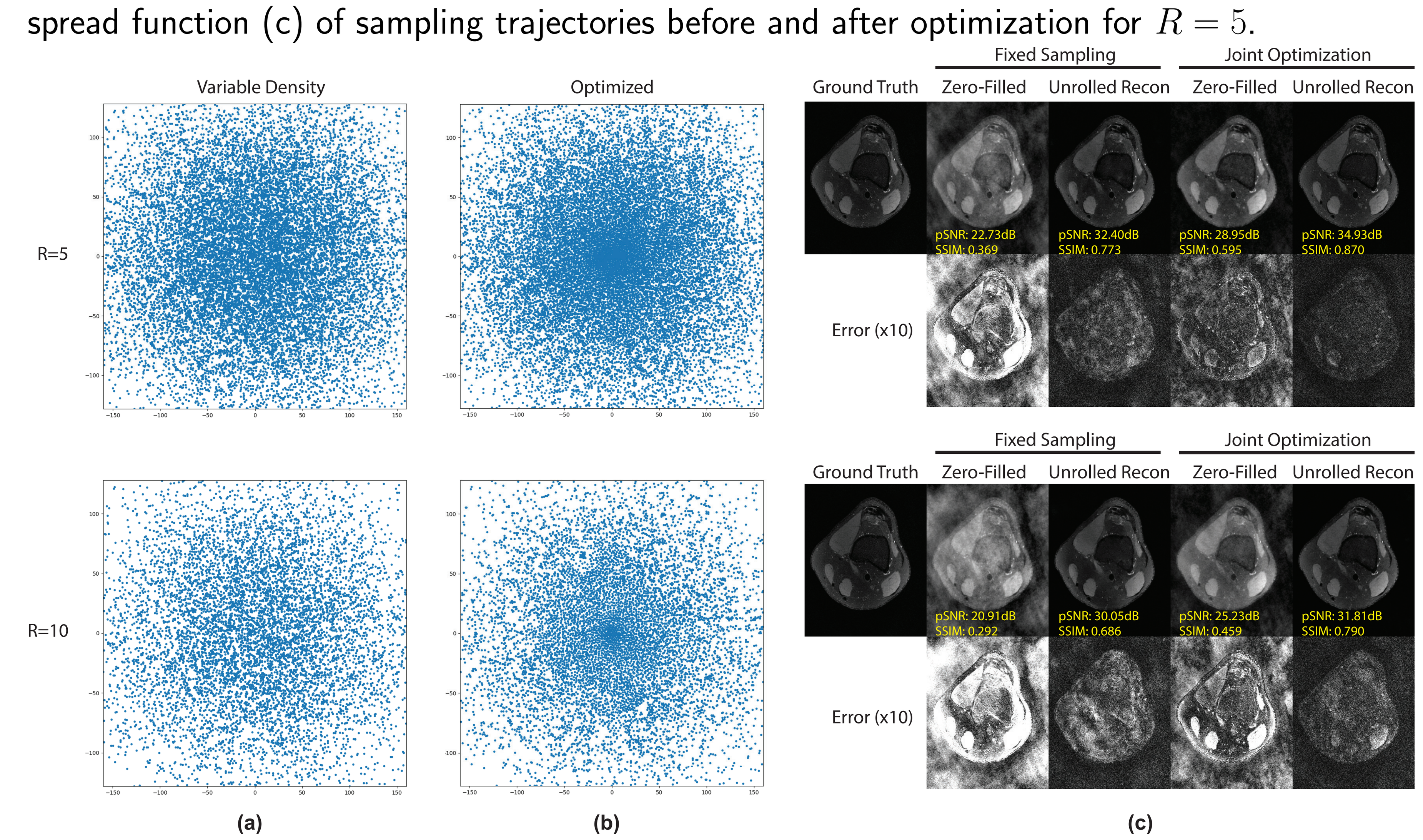

Figure 3: Variable density (a) and optimized (b) trajectories along with the reconstruction result on a slice in the test set (c). Zero-filled reconstruction corresponds to applying A_ϕ^H on z directly.

Conclusion

- We use variational information maximization for learning the sampling pattern in MRI jointly with image reconstruction.
- Optimizing sampling pattern improves reconstruction quality highlighting benefits that can be obtained by learning undersampling patterns.