Universal Generative Modeling For Calibration-free Parallel MR Imaging

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Abstract

The integration of compressed sensing and parallel imaging (CS-PI) provides a robust mechanism for accelerating MRI acquisitions. However, most such strategies require the explicit formation of either coil sensitivity profiles or a cross-coil correlation operator, and as a result reconstruction corresponds to solving a challenging bilinear optimization problem. In this work, we present an unsupervised deep learning framework for calibration-free parallel MRI, coined universal generative modeling for parallel imaging (UGM-PI). More precisely, we make use of the merits of both wavelet transform and the adaptive iteration strategy in a unified framework. We train a powerful noise conditional score network by forming wavelet tensor as the network input at the training phase. Experimental results on both physical phantom and in vivo datasets implied that the proposed method is comparable and even superior to state-of-the-art CS-PI reconstruction approaches.

Method

For the neural network trained by wavelet tensor X, the reconstruction result is obtained via gradually annealed noise. i.e.,

$$X_j^t = X_j^{t-1} + \frac{\alpha_i}{2} S_\theta(X_j^{t-1}, \sigma_i) + \sqrt{\alpha_i}\, z_t$$

Specifically, at each iteration of the annealed Langevin dynamics, we update the solution via data consistency constraint, let $x^t = T_w^{-1}(X^t)$, it yields,

$$x_j^{t+1} = \arg\min_x \left\{ \sum_{j=1}^{J} \left\| F_m x_j - y_j \right\|_2^2 + \lambda \left\| x_j - x_j^t \right\|_2^2 \right\}$$

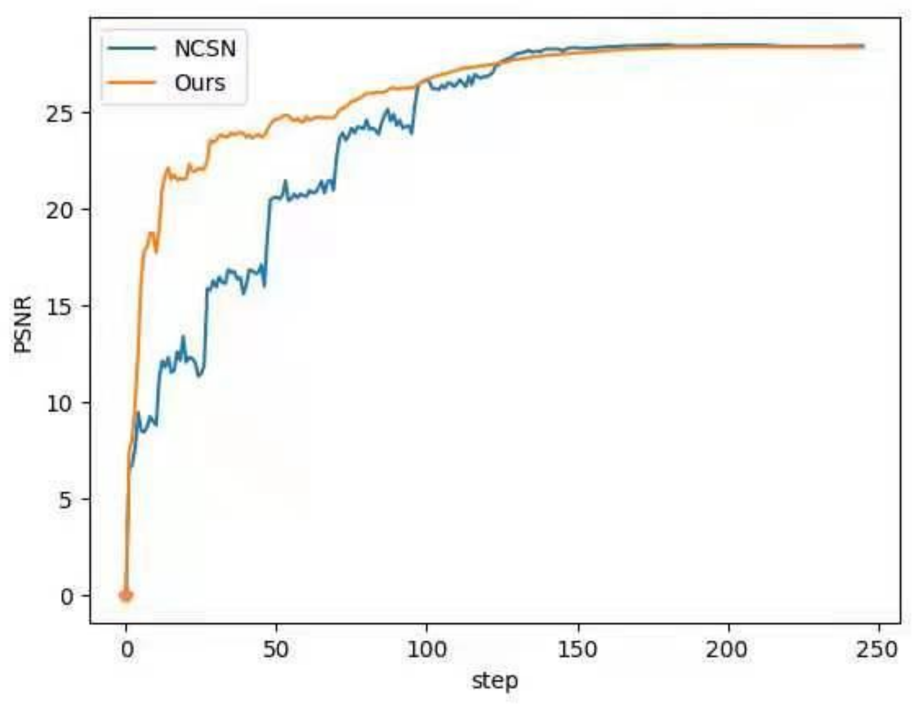
The least-square (LS) minimization can be solved as follows:

$$(F_m^T F_m + \lambda) x_j^{t+1} = F_m^T y_j + \lambda x_j^t$$

Let $F \in C^{M \times M}$ denotes the full Fourier encoding matrix which is normalized as $F^T F = 1_M$. $Fx_j(k_v)$ stands for the updated j-th coil value at under-sampled k-space location k_v, and Ω represents the sampled subset of data, it yields,

$$Fx_j(k_v) = \begin{cases} Fx_j^t(k_v), & k_v \notin \Omega \\ \dfrac{FF_m^T y_j(k_v) + \lambda Fx_j^t(k_v)}{(1+\lambda)}, & k_v \in \Omega \end{cases}$$

The benefit of constructing deep learning priors in wavelet domain is visualized as follow:



Even if the final reconstruction result is similar, the introduction of the deep gradient of prior in higher-dimensional wavelet space enables the learning model to reach the convergence target more quickly.

Fig.1. Convergence tendency comparison in the native NCSN and the advanced UGM-PI, respectively.

Code

For the convenience of reproducibility, code of UGM-PI is available at: https://github.com/yqx7150/UGM-PI.

Network Architecture

We propose a more flexible and more universal unsupervised deep learning framework for calibration-free parallel MRI. The input of the network is multi-channel and multi-scale wavelet tensor obtained from the fully sampled single-channel MR data, and the output is the gradient of data density. Moreover, the trained model can be used for PI reconstruction scenarios with any coil number.

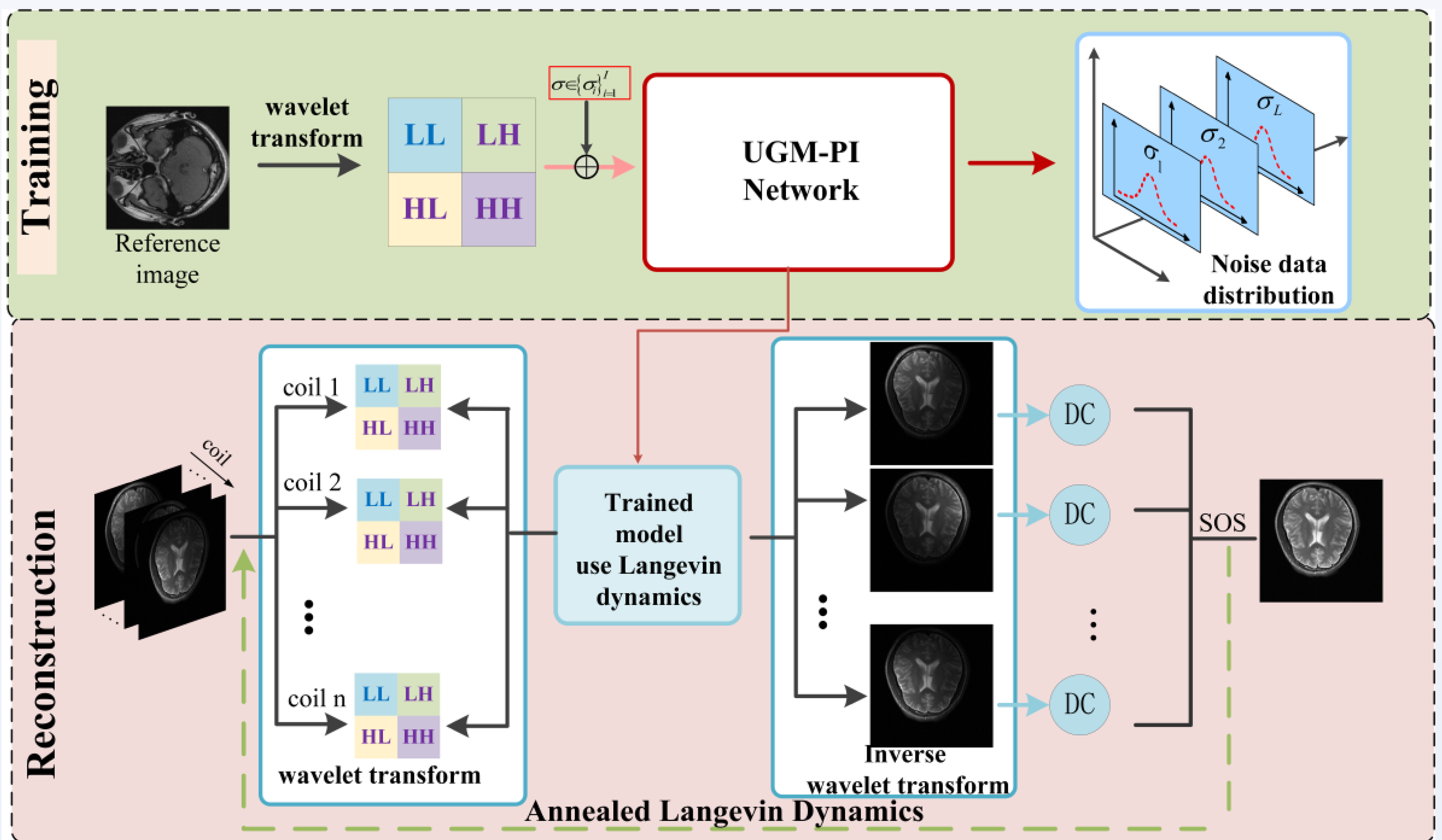


Fig.2. Flowchart illustration of the proposed UGM-PI model. Top: Network training process in single coil image for prior learning. Bottom: An intermediate result of the iterative process at multi-coil MRI reconstruction phase.

Experimental Results

- **Sampling masks:** 2D random under-sampling with the variable density pattern, and 2D Poisson disk under-sampling
- **Compared methods:** P-LORAKS, SAKE, and learn joint-sparse codes for calibration-free parallel MR imaging (LINDBREG)

Table 1. Average PSNR, SSIM and HFEN Values of Reconstruction Results.

		P-LORAKS	SAKE	LINDBREG	UGM-PI
Random _2D	R=4	35.94	35.95	33.49	**40.13**
		0.92	0.88	0.93	**0.95**
		0.50	0.57	0.63	**0.40**
	R=6	32.73	33.62	30.79	**37.25**
		0.88	0.84	0.90	**0.93**
		0.65	0.80	0.80	**0.53**
Poisson _2D	R=6	33.61	34.96	32.47	**38.05**
		0.90	0.87	0.92	**0.95**
		0.48	0.57	0.59	**0.42**
	R=10	31.22	32.13	28.67	**34.20**
		0.85	0.82	0.84	**0.91**
		0.83	0.94	1.19	**0.71**

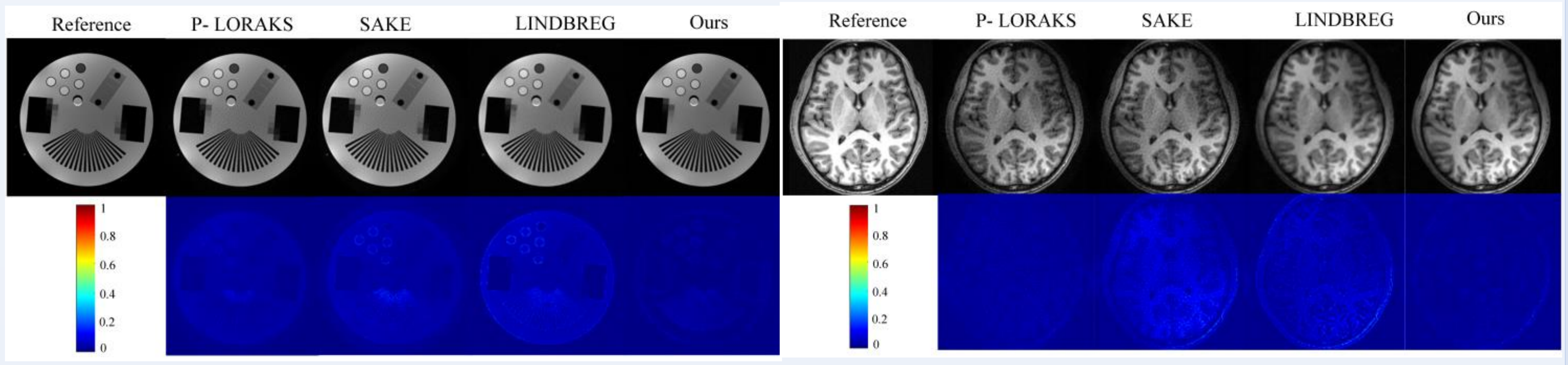


Fig.3. Reconstruction comparison by P-LORAKS, SAKE, LINDBREG, and UGM-PI under two different sampling masks.

Conclusion

- we present an universal generative modeling for parallel imaging. Although the learned prior knowledge is trained from single coil image, it can be used for PI reconstruction with any coil number.
- we make use of the merits of wavelet transform at prior learning stage and the adaptive iteration strategy at the reconstruction stage, respectively.
- Compared with three state-of-the-art calibration-free methods, the proposed method produces images with less noise and artifacts.