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Universal Generative Modeling for Calibration-Free Parallel MR Imaging

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Universal Generative Modeling for Calibration-Free Parallel MR Imaging

Outline

1 Introduction

2 Method

3 Experimental Results

4 Conclusion

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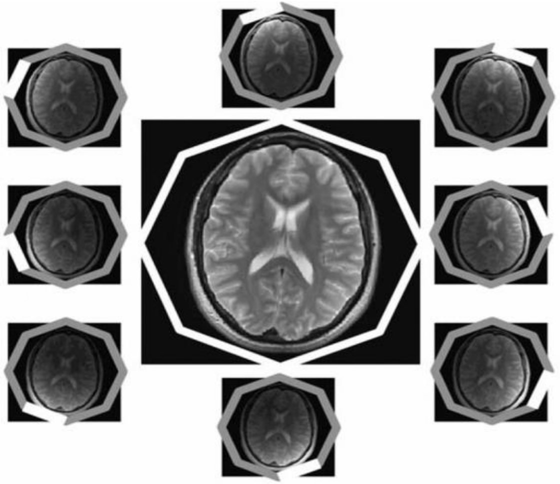
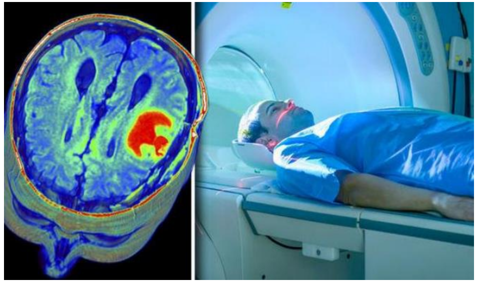
Background





Challenging:

Most parallel imaging 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.

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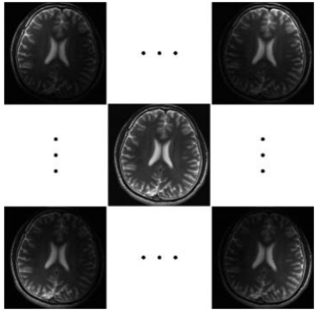
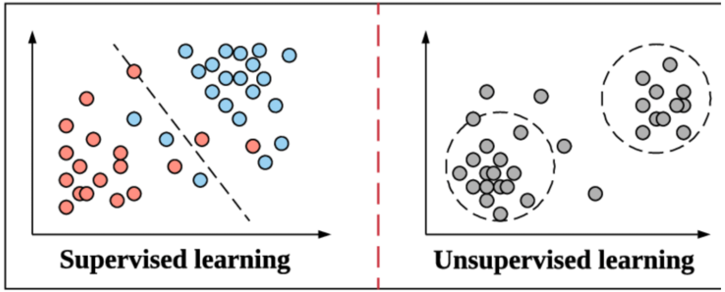
Exploring

There are mainly two categories of deep learning-based fast MRI: Supervised and unsupervised schemes.





Disadvantage:

1、 Requiring a huge number of labeled samples.

2、 Adding a layer of complexity when dealing with multi-coil data.

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Contribution

- **Universal generative modeling:** Although the learned prior knowledge is **trained from single coil image**, the proposed model can be used for **PI reconstruction with any coil number**.

- **Reconstruction with fast mixing:** Due to the special similarity among the multi-channel object, an **adaptive iteration strategy** for reducing the iteration number of the inner loop is introduced.

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Network Architecture

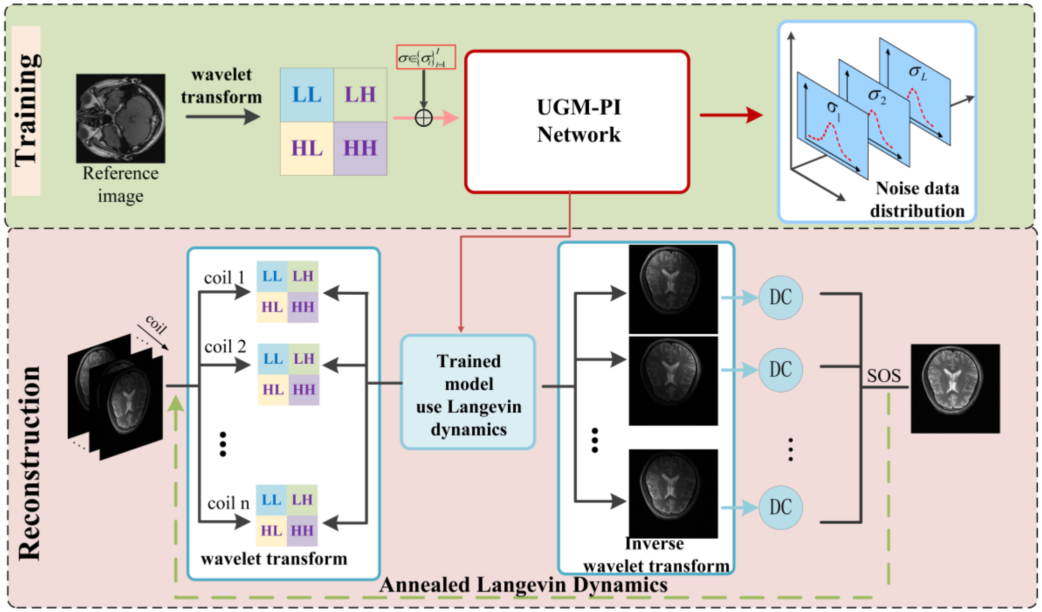

Fig. 2. Flowchart illustration of the proposed UGM-PI model.

Algorithm 1 UGM-PI

Training stage

Dataset: Dataset in wavelet domain: $X = \{x_{ll}, x_{lh}, x_{hl}, x_{hh}\}$

Output: Trained UGM-PI $S_\theta(X,\sigma)$

Reconstruction stage

Setting: $\sigma \in \{\sigma_i\}_{i=1}^{I}$, ε, T, x^0, k_v and Ω

1: **for** $i \leftarrow 1$ to I **do (Outer loop)**

2: $\alpha_i = \varepsilon \cdot \sigma_i^2 / \sigma_I^2$

3: **for** $t \leftarrow 1$ to T **do (Inner loop)**

4: $X_j^t = T_W(x_j^t)$

5: Draw $z_t \sim N(0,1)$ and $X^{t-1} = \{x_{ll}^{t-1}, x_{lh}^{t-1}, x_{hl}^{t-1}, x_{hh}^{t-1}\}$

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

7: Update $x_j^t = T_W^{-1}(X_j^t)$ and Eq. (10)

8: **end for**

9: $x_j^0 \leftarrow x_j^T$

10: Update multi-coil images x_j^T, $j = 1, \cdots, J$

11: **end for**

12: Update the final image as the square root of $SOS(x_j^T)$

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Reconstruction with universal deep prior

For the neural network trained by high dimensional 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:

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

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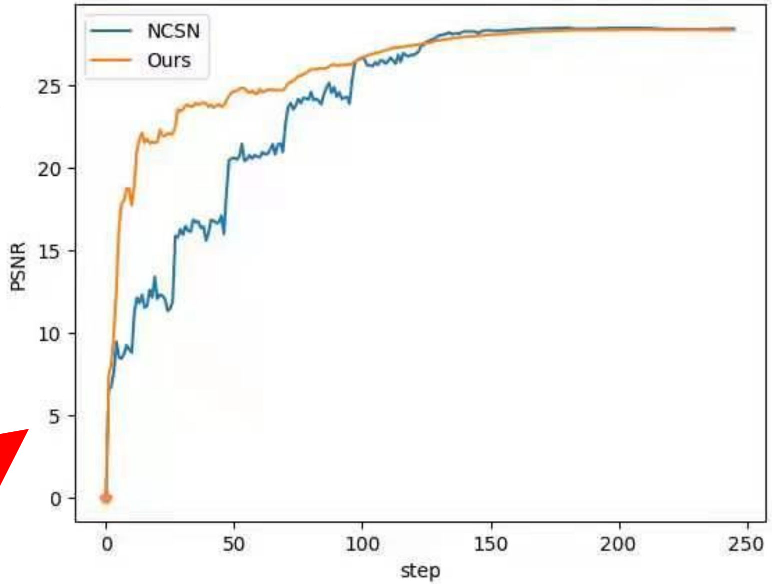
Convergence tendency comparison

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

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



It shows the convergence tendency of PSNR curves versus iteration that reconstructed by UGM-PI and the native NCSN. Even if the final reconstruction result is similar, UGM-PI **reach the convergence target more quickly**.

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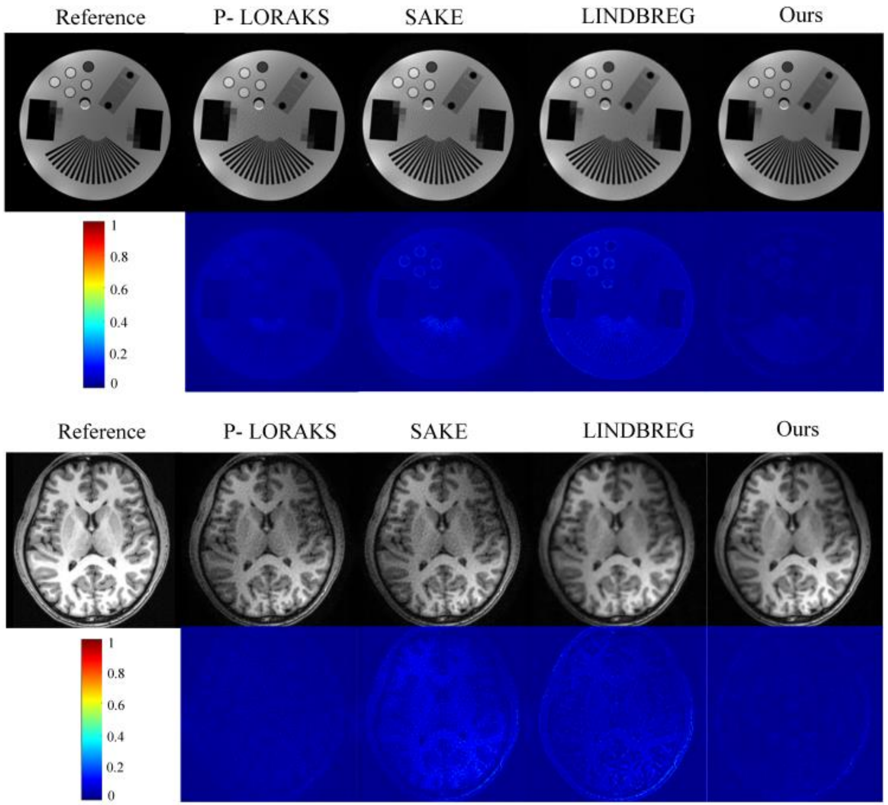
Comparative Experiment

Average PSNR,SSIM and HFEN comparison values and reconstruction results with three state-of-the-art methods.

		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**



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Conclusion

1、we present a **universal generative modeling** for parallel imaging, it can be used for PI reconstruction with any coil number.

2、we made use of the merits of **wavelet transform** at prior learning stage and the **adaptive iteration strategy** at the reconstruction stage.

3、Compared with state-of-the-art calibration-free methods, the proposed method can produce images with **less noise and artifacts**.

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THANK YOU