Zero-shot Low-field MRI Enhancement via Denoising Diffusion Driven Neural Representation

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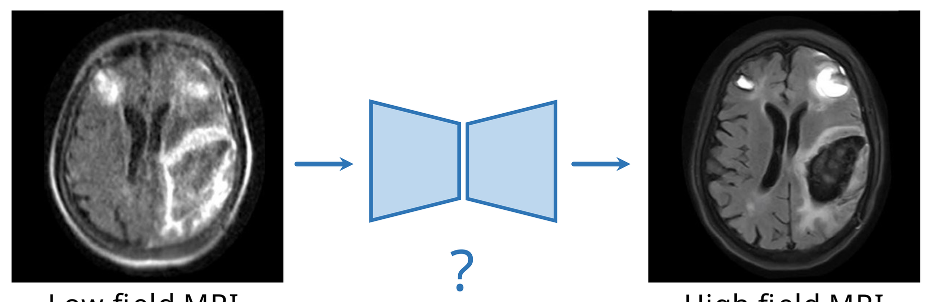
Introduction

- **Main Challenges:** Low-field (LF) MRI holds promise for MRI techniques to new heights that are ***affordable***, ***portable***, and ***site-agnostic***. However, it is inevitably constrained by **low SNR and contrast**, posing challenges for practical diagnostic research.
- **Objective:** To enhancement low-field MRI quality to high-field levels.



- **Solution:** Decomposing the problem into (1) ***Data-Prior*** (2) ***Data-Fidelity*** sub-problems and solving in an iterative framework united by Diffusion Model [1] and Implicit Neural Representations (INR) [2].

Methodology

Overview: We decompose the LF MRI enhancement problem into a data-fidelity and a data-prior sub-problems. The data-prior sub-problem is solved by reverse sampling using a pre-trained **diffusion model**, while the data-fidelity sub-problem is solved by **INR** with embedded degradation models and a strong continuity prior.

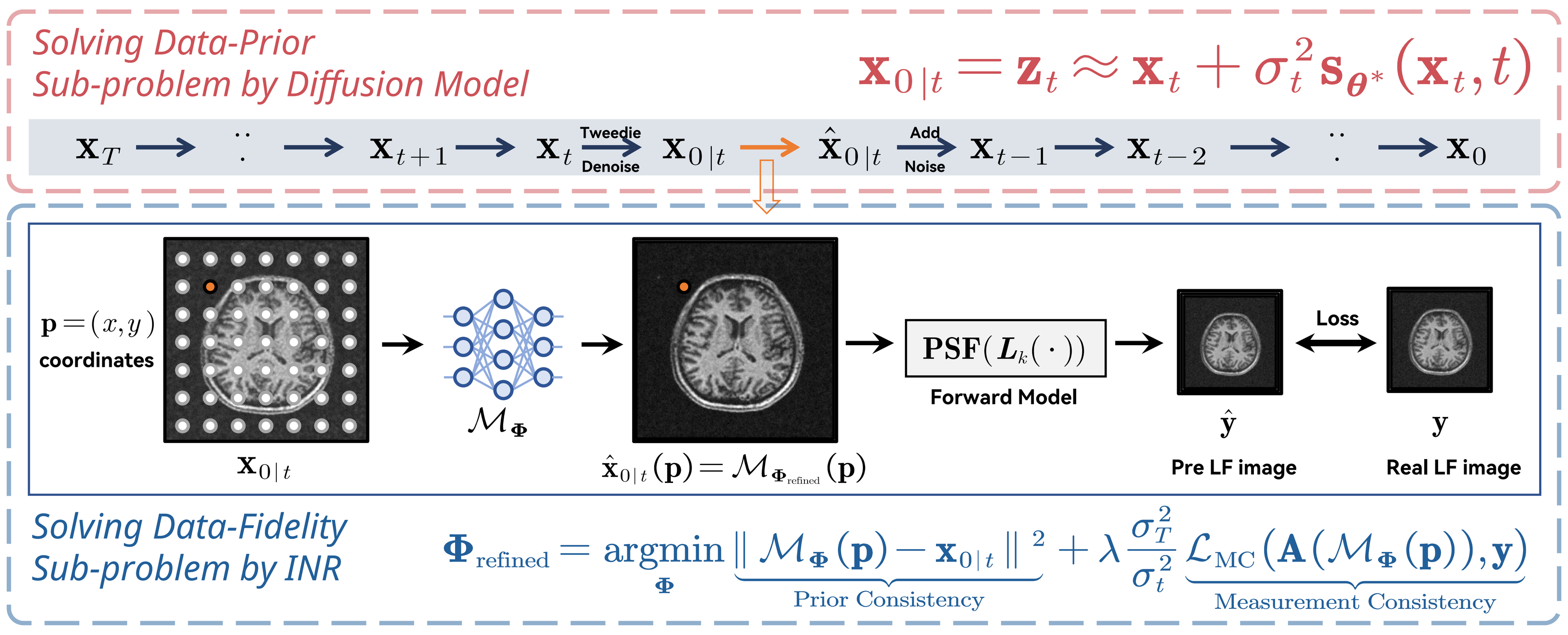


Fig. 1: Overview of the proposed DiffDeuR.

(a) Degradation Model: Inspired by the insights of [3], we approximate the degradation model from HF MRI to LF MRI as a combination of downsampling, blurring (Gaussian point spread function (PSF) blurring), and noise addition as follow:

$$\mathbf{x}_{\text{LF}} = \mathbf{PSF}(\boldsymbol{L}_k(\mathbf{x}_{\text{HF}})) + \mathbf{n}$$

(b) Problem Formulation: For the challenging ill-posed inverse problem of recovering HF MRI from LF MRI, we model the solution as a regularized inverse problem as:

$$\hat{\mathbf{x}} = \underset{\mathbf{x}}{\text{argmin}} \frac{1}{2\sigma^2} \| \mathbf{y} - \mathbf{PSF}(\boldsymbol{L}_k(\mathbf{x})) \|^2 + \lambda \cdot \mathcal{R}(\mathbf{x}),$$

then we decoupling the data fidelity and data prior terms using *Half Quadratic Splitting (HQS)* and transform them to two distinct sub-problems as follows:

$$\begin{cases} \mathbf{z}_t = \underset{\mathbf{z}_t}{\text{argmin}} \dfrac{1}{2(\sqrt{\lambda/\mu})^2} \| \mathbf{z}_t - \mathbf{x}_t \|^2 + \mathcal{R}(\mathbf{z}_t) \\ \mathbf{x}_t = \underset{\mathbf{x}_t}{\text{argmin}} \| \mathbf{y} - \mathbf{PSF}(\boldsymbol{L}_k(\mathbf{x}_t)) \|^2 + \mu \sigma_i^2 \| \mathbf{x}_t - \mathbf{z}_{t-1} \|^2 \end{cases}$$

(c) Alternating Optimization: We solve the two sub-problems alternately in an iterative framework. Specially:

- Data-Prior Sub-problem: As it is essentially a Gaussian denoising problem, we propose to use the diffusion model sampling with Tweedie's formula as the denoiser to solve it.
- Data-Fidelity Sub-problem: Inspired by [4], we use a model-driven INR framework to learn a continuous function that maps spatial coordinates to intensities that simultaneously conform to both the data prior manifold and the measurement manifold.

Results

■ Experiments on *simulated data*

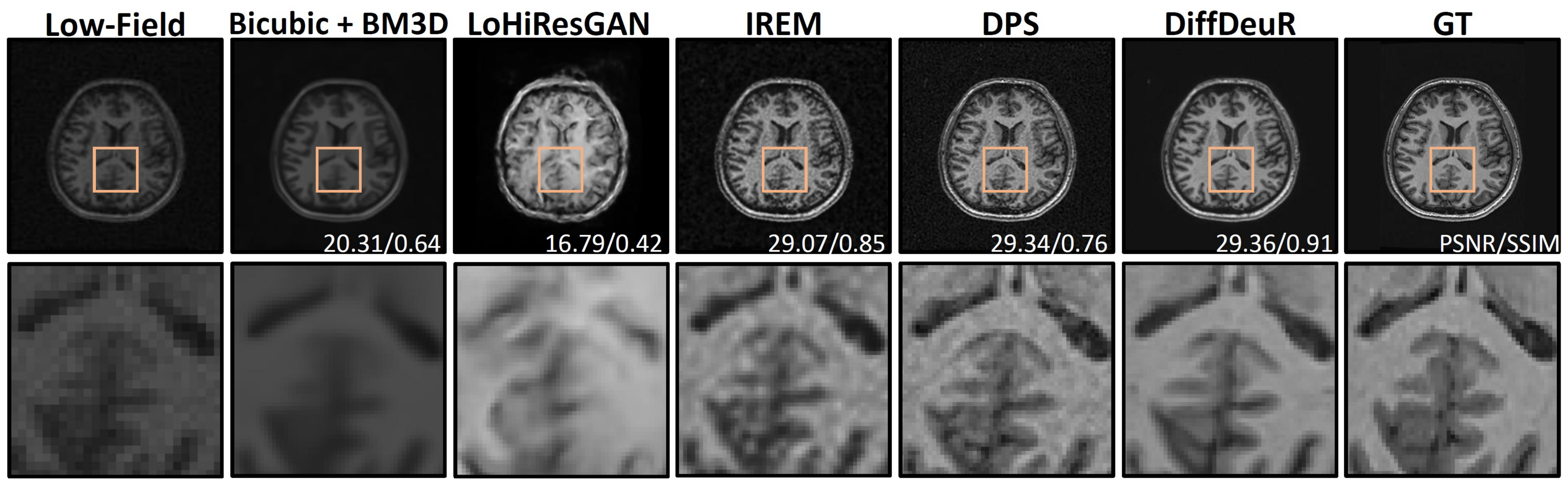


Fig. 2: Qualitative results of methods in comparison on simulated LF MRI.

Table. 1: Quantitative results of methods in comparison on simulated LF MRI.

Method	PSNR	SSIM	LPIPS
Bicubic+BM3D [6]	20.708±0.606	0.6747±0.008	0.2665±0.024
LoHiResGAN [10]	18.015±0.707	0.3909±0.013	0.2718±0.015
IREM [28]	27.019±0.255	0.8236±0.004	0.1839±0.010
DPS [2]	27.717±0.359	0.8198±0.007	0.1632±0.012
DiffDeuR (Ours)	28.130±0.264	0.9146±0.004	0.0905±0.007

■ Experiments on *real data*

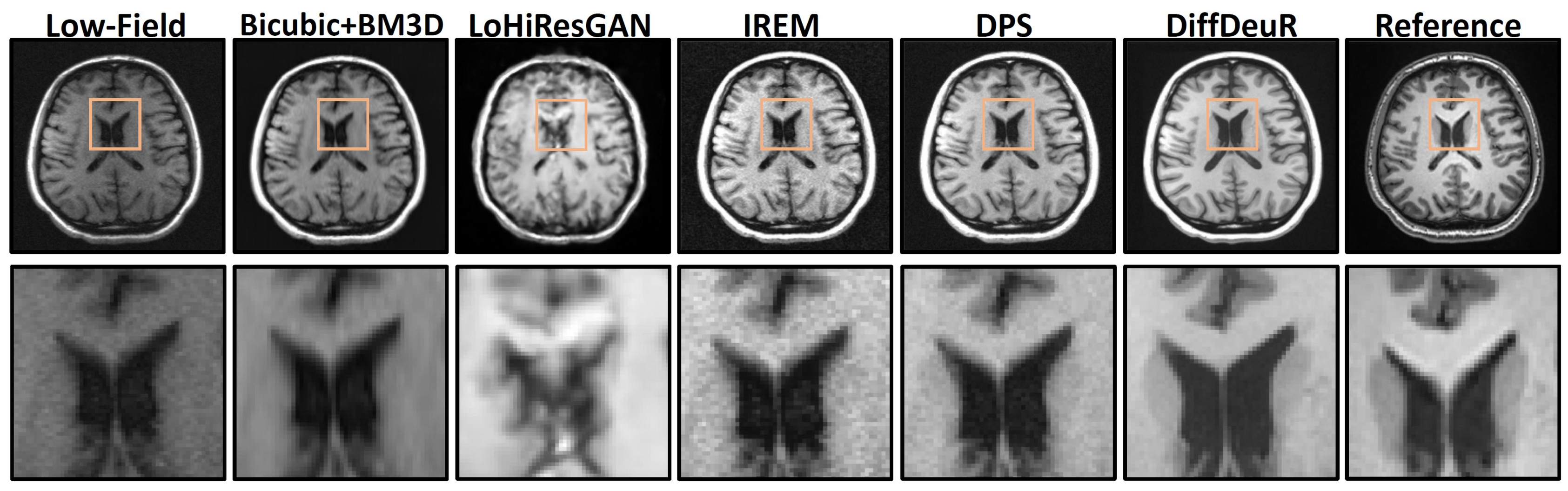


Fig. 3: Qualitative results of methods in comparison on real 0.2 T LF MRI with 1×1mm² resolution.

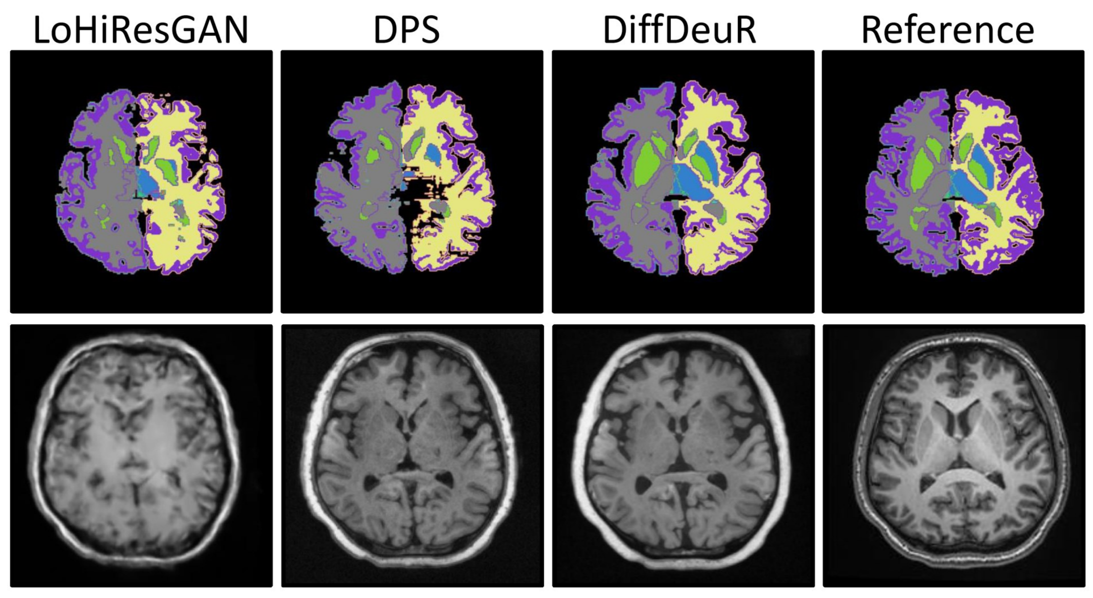


Fig. 4: Qualitative results of whole brain segmentation on real 0.2 T LF MRI with 3×3mm² resolution.

Summary

- This work proposes DiffDeuR, an unsupervised method that innovatively employs the HQS framework to combine the diffusion model with INR, leveraging the strengths of both to tackle the challenging task of LF MRI enhancement.
- The comprehensive evaluation on simulation and real datasets validates the superior performance of our DiffDeuR model compared with SOTA methods in LF MRI enhancement.

Reference

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