Proceedings Article

Degradation Consistent Conditional Diffusion Model with Frequency Alignment for 3D Mag-netic Particle Image Enhancement

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Abstract

Magnetic Particle Imaging (MPI) provides quantitative visualization of magnetic nanoparticle distributions but suffers from limited spatial resolution and anisotropic blurring due to system nonlinearities and hardware imperfections. To address the low-resolution issues caused by various noise sources, we propose a Degradation-Consistent Conditional Diffusion Model (DCCDM) for three-dimensional (3D) MPI image super-resolution. The proposed model introduces two physically interpretable constraints: a degradation-consistency loss, utilizing a degradation operator to ensure that the reconstructed high-resolution volume remains consistent with the observed low-resolution data, without requiring a known system matrix, and a frequency-alignment regularization, enforcing structural fidelity in the low-frequency band and detail enhancement in the high-frequency band. Experiments on simulated 3D MPI datasets demonstrate that DCCDM achieves superior performance compared with existing CNN-, GAN-, and diffusion-based models.

I. Introduction

High-quality resolution enhancement methods in Magnetic Particle Imaging (MPI) typically rely on modeling the one-dimensional (1D) raw signal domain [1], where the physical forward process is explicitly represented. In contrast, image-domain learning-based methods often overlook these physical constraints, leading to suboptimal reconstruction fidelity and reduced generalizability. Recently, diffusion probabilistic models have shown remarkable generative ability and stability for inverse problems such as denoising on PET, MRI images [2]. However, most diffusion models assume an explicit forward operator [3], which is often unavailable in MPI. To address these issues, we propose a 3D degradation consistent conditional diffusion model (DCCDM) that incorporates physical constraints without the need for a known system matrix. We introduce a degradation consistency constraint to enforce observational fidelity by simulating the MPI degradation process through a differentiable operator. Designing a frequency-alignment regularization that aligns the predicted and reference images in the frequency domain, balancing low-frequency structural accuracy and high-frequency detail recovery.

II. Methods

The 3D vascular dataset from MedMNIST [4] is used as the original Magnetic Nanoparticles (MNPs) concentration distribution. Field-Free Point (FFP) scanning imaging is simulated by performing layered scanning and
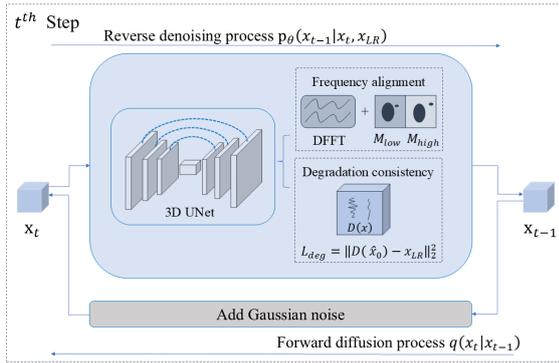
Figure 1: DCCDM Architect Overview.

Table 1: Quantitative Evaluation on Simulation Dataset.

Method	PSNR	SSIM	RMSE
EDSR	30.704	0.636	7.626
3D-UNet	30.376	0.837	7.940
ESRGAN	31.237	0.968	6.989
3D DDPM	34.772	0.972	4.709
DCCDM	**36.065**	**0.981**	**3.982**

varying the driving field frequency along a Cartesian trajectory. The acquired 3D MPI images are used as the source domain, while the original 3D phantom images, consisting of 1,100 images ($32\times32\times32$), serve as the target domain for training.

Given a pair of low-resolution and high-resolution MPI volumes $(x_{LR}, x_{HR}) \in \mathbb{R}^{1\times32\times32\times32}$, the proposed model learns to reconstruct high-resolution volumes conditioned on low-resolution inputs through a 3D conditional diffusion process [2]. The forward diffusion process gradually perturbs the high-resolution target x_{HR} into noisy samples x_t, the reverse process predicts the noise $\epsilon_\theta(x_t, x_{LR}, t)$ conditioned on the low-resolution image x_{LR}. To ensure physical consistency, the overall training objective combines the standard diffusion loss with physically guided regularization terms, including degradation consistency and frequency-domain alignment.

II.I. Degradation Consistency Constraint

Inspired by the Diffusion Posterior Sampling (DPS) framework [5], we introduce a degradation consistency constraint to ensure that the generated image remains physically plausible without an explicit MPI system matrix. We approximate the degradation operator $A(\cdot)$ by a differentiable surrogate $D(\cdot)$:

$$D(x) = \mathcal{U}(\mathcal{P}_2(\mathcal{G}_3(x))) \quad (1)$$

Where $\mathcal{G}_3$ denotes 3D Gaussian blurring, $\mathcal{P}_2$ is 2× downsampling, and $\mathcal{U}$ is trilinear upsampling. It enforces that the degraded reconstruction should match the observable low-resolution measurement.

II.II. Frequency Alignment Regularization

To further enhance structural fidelity and preserve fine details, we introduce a frequency-alignment loss that constrains the predicted and reference images in the 3D

frequency domain. Let $\mathcal{F}(\cdot)$ denote the 3D Fourier transform, then the loss is:

$$
\begin{aligned}
L_{freq} &= \left\| M_{low} \bigodot (\mathcal{F}(\hat{x}_0) - \mathcal{F}(x_{LR})) \right\|_1 \\
&\quad + \gamma \left\| M_{high} \bigodot (\mathcal{F}(\hat{x}_0) - \mathcal{F}(x_{HR})) \right\|_1 \quad (2)
\end{aligned}
$$

Where M_{low} and M_{high} are spherical binary masks representing the low- and high-frequency bands, and γ controls the high-frequency emphasis, which is empirically set to 0.3 based on parameter experiments.

III. Results

Table 1 presents the quantitative comparison among several state-of-the-art super-resolution models, including 3D U-Net, EDSR [6], ESRGAN [7], 3D-DDPM [2]. DCCDM achieves the highest PSNR and SSIM while maintaining the lowest RMSE, outperforming all competing approaches. Although Gaussian noise is used in simulation, DCCDM does not explicitly assume a specific noise distribution, and the proposed framework is expected to generalize to more complex noise conditions. These results collectively validate the effectiveness and robustness of the DCCDM in preserving fine structural details and improving reconstruction fidelity.

IV. Conclusion

We propose DCCDM for 3D MPI resolution enhancement. By introducing a physics-inspired degradation consistency constraint and a frequency-alignment regularization, it achieves an effective trade-off between data fidelity and structural detail preservation, without relying on explicit system matrix modeling. While diffusion-based inference is computationally more expensive than single-pass CNNs, the proposed DCCDM is suitable for offline or high-fidelity MPI image enhancement scenarios, where image quality is prioritized. Experimental results demonstrate that DCCDM significantly outperforms existing methods, validating its effectiveness and robustness.

Acknowledgments

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