International Journal on Magnetic Particle Imaging
Vol 11, No 1, Suppl 1, Article ID 2503068, 3 Pages

Infinite Science Publishing

Proceedings Article

A score-based model guided by signals for magnetic particle imaging reconstruction

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Abstract

Magnetic particle imaging (MPI) can reconstruct the distribution of magnetic nanoparticles (MNPs) from their nonlinear response signals. The traditional system matrix (SM) reconstruction method requires solving an ill-posed inverse problem using hand-crafted regularization terms that demand careful parameter tuning. Here, we proposed a score-based model guided by signals for MPI reconstruction. The measured response signals were embedded to guide the score-based model in sampling specific MPI images from noise. Simulated experiments showed that our proposed method improved the reconstruction quality in the presence of variable noise levels.

I. Introduction

The system matrix (SM) needs to be calibrated and is subsequently used to solve an ill-posed linear inverse problem for SM-based magnetic particle imaging (MPI) reconstruction. Hand-crafted regularization terms are helpful for solving inverse problems, but they may introduce bias to images and need thorough parameter tuning. Recently, some deep learning-based methods in MPI reconstruction [1, 2] used end-to-end neural networks to directly fit the mapping between response signals to MPI images, or combined traditional iterative methods with learning-based priors. However, the performance of deep learning-based methods is still not satisfactory, especially in contexts where the background noise is variable [3].

In this paper, we proposed a score-based model guided by signals for MPI reconstruction. Our proposed method utilized the information from response signals to guide the score-based model in learning the distribution of MPI images under corresponding signals, rather than establishing a direct mapping from response signals to MPI images. Therefore, our proposed method enabled response signals to guide the trained score-based model in sampling specific images for MPI reconstruction.

II. Methods

II.I. Score-based model guided by signals

In this work, we reformulated MPI reconstruction as a sampling process using the score-based model guided by response signals [4], expressed as:

$$dx = \left[f(x,n) - g^2(n) \nabla_x \log p_n\ (x \mid b) \right] dn + g(n)\, dw \tag{1}$$

where x denotes the sampled image, n denotes the index of sampling iterations, b denotes the response signals of magnetic nanoparticles (MNPs), $f(\cdot)$ denotes the drift function, $g(\cdot)$ denotes the diffusion function,

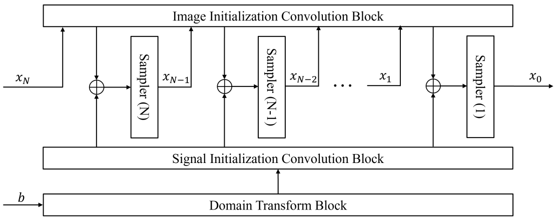

Figure 1: The overall flowchart of the sampling process.

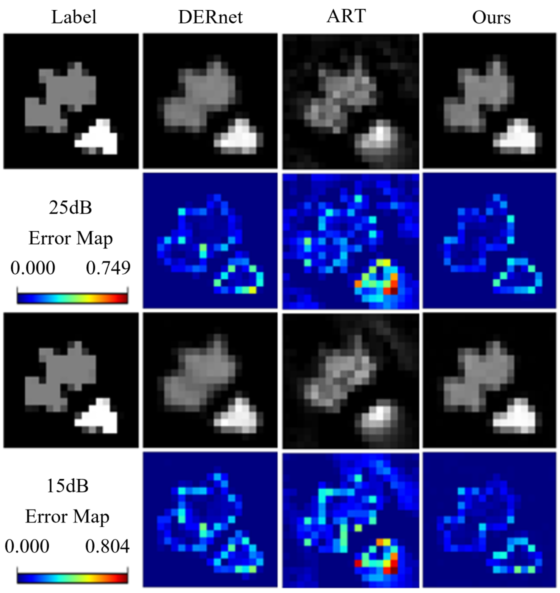

Figure 2: Simulated experimental results with the noise level of 15 dB and 25 dB for MPI reconstruction.

w denotes the reverse standard Brownian motion, and $\nabla_x \log p_n\ (x \mid b)$ denotes the score function of the posterior distribution $p_n(x \mid b)$, which characterizes the distribution of the sampled image x at the n-th sampling iteration conditioned on the specific response signals b. Noting that obtaining the score function $\nabla_x \log p_n\ (x \mid b)$ is not tractable. We used the Sampler module to approximate the score function with denoising score matching [4] and calculate the sampled image using (1) (see Fig. 1).

II.II. Datasets

We approximate the MPI frequency-domain forward model as a linear model with additive noise to simulate response signals [5], expressed as:

$$b_s = A_f x_s + noise_s \tag{2}$$

where $A_f \in C^{M\times N}$ denotes the measured SM after background signal removal, $x_s \in R^N$ denotes the simulated distribution vector of MNPs, and $noise_s \in C^M$ denotes the simulated noise. Then, we select the two-dimensional SM of size 19×19 from OpenMPI dataset [6], after subtracting background signals and filtering out frequency components with a signal-to-noise ratio (SNR) less than 5 to form A_f. Additionally, label images from a tumor phantom dataset (i.e., the ground truth) are flatten into vectors as x_s. The Gaussian noise with different power levels is selected as $noise_s$ to control the SNR of simulated signals [7].

III. Results and discussion

Our proposed method is compared with representative traditional and deep learning-based reconstruction methods, as shown in Fig. 2. Images reconstructed by the algebraic reconstruction technique (ART) exhibited significant artifacts and noise. Compared to ART, DERnet [1] showed improved reconstruction performance but failed to preserve edges. In contrast, our proposed method achieved superior performance at all SNRs with reduced noise, lower errors, and better edge preservation. And an image of size 19×19 can be reconstructed in 2.49 seconds using our proposed method on a single RTX 4090 GPU.

IV. Conclusion

In this work, a score-based model guided by response signals was designed for MPI reconstruction. Embedded MPI response signals can guide the score-based model in sampling images under corresponding signals. The simulated experiments demonstrated that our proposed method achieved improved performance in MPI reconstruction.

Author's statement

This work was supported by the National Natural Science Foundation of China under Grant: 92359304, 62027901, U23A6011, 81227901. Beijing Natural Science Foundation: JQ22023; CAS Youth Innovation Promotion Association under Grant Y2022055. Authors state no conflict of interest.

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10.18416/ijmpi.2025.2503068