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Progressive conditional diffusion for system matrix synthesis in magnetic particle imaging

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Abstract

Acquiring the system matrix (SM) under high-gradient fields in Magnetic Particle Imaging remains challenging, as it requires prolonged high-current operation. To overcome this limitation, we introduce a novel approach that synthesizes the high-gradient SM from its easier-to-obtain low-gradient counterpart using a conditional diffusion model. A progressive conditioning decay strategy is employed to effectively steer the generation of the high-gradient SM. Simulation results demonstrate that our method can successfully synthesize high-gradient SMs, thereby reducing the acquisition burden.

I. Introduction

Magnetic particle imaging (MPI) is a novel imaging modality offering notable advantages such as high sensitivity, high spatial resolution, and radiation free [1, 2]. For MPI systems, achieving a larger selection field gradient combined with system matrix (SM)-based reconstruction [3] holds the potential to yield superior spatial resolution. However, acquiring the SM under high gradient strengths remains challenging, particularly for systems utilizing electromagnets, which require sustaining high currents over extended periods during SM calibration. Considering the inherent similarity between SMs acquired under low and high gradient strengths within the same system, this work employs a diffusion model [4] to generate SM under high-gradient magnetic fields. Specifically, the low-gradient SM is utilized as conditioning to guide the generation of its high-gradient counterpart. To prevent the conditional information from excessively dominating the sampling trajectory and thereby constraining the model's ability to synthesize high-gradient features, a progressive conditioning decay strategy is introduced. During training, the influence of the condition is gradually attenuated, and it is randomly dropped with a certain probability, enabling the model to learn to generate unconditionally. Moreover, noise of equivalent magnitude is added to the conditional inputs to improve the model's robustness against perturbations.

II. Methods

II.I. Datasets

We constructed a paired dataset of SMs under high and low gradient fields. The low-gradient SM served as the conditional input, and the high-gradient SM as the generation target. The gradient strengths were 1 $\mathrm{T/m}/\mu_0$ and 0.1 $\mathrm{T/m}/\mu_0$, with excitation amplitudes of 20 mT and 2 mT, respectively, resulting in a unified field of view. Simulations were performed using particle core diameters ranging from 30 nm to 70 nm in 10 nm increments,

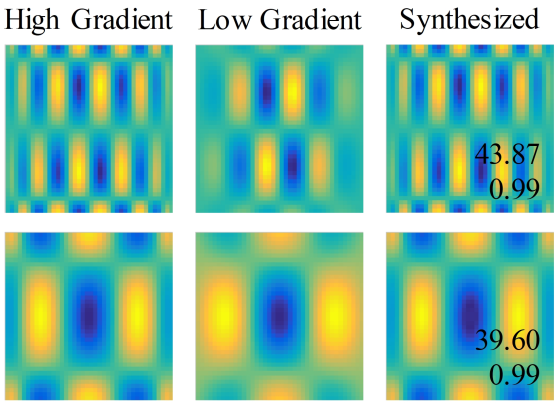

Figure 1: High-Gradient, low-Gradient, and synthesized SM, with PSNR and SSIM values displayed on the synthesized SM.

Algorithm 1 Training

Require: Dataset $D = \{(x_0, y)\}$, unconditional probability p_{uncond}, network f_θ, total timesteps T, $\{\bar{\alpha}_t\}_{t=1}^T$

for each training step **do**
  $(x_0, y) \leftarrow \text{next\_batch}(D)$ ▷ Sample a mini-batch
  $t \sim \text{Uniform}(\{1, \ldots, T\})$ ▷ Sample a timestep
  $\epsilon \sim N(0, I)$ ▷ Sample Gaussian noise
  if random() $< p_{\text{uncond}}$ **then**
    $y \leftarrow y_{\text{null}}$
  end if
  $x_t \leftarrow \sqrt{\bar{\alpha}_t}\, x_0 + \sqrt{1-\bar{\alpha}_t}\, \epsilon$ ▷ Noisy data at timestep t
  $\epsilon_\theta \leftarrow f_\theta(x_t, t, y)$ ▷ Predict noise
  $L \leftarrow \|\epsilon - \epsilon_\theta\|^2$ ▷ Compute loss
end for

following a Lissajous scanning trajectory [5]. The excitation frequency f_x varied from 10 kHz to 30 kHz in 10 kHz steps, while the frequency f_y was determined by $f_y = N_d/(N_d+1) \times f_x$, where the number of N_d ranged from 49 to 99 with a step of 10. A total of 54 pairs of SMs were generated, each comprising 168 harmonic components and corresponding to 9072 paired data points.

II.II. Conditional Diffusion with Progressive Condition Perturbation

Our method employs a conditional diffusion framework with stochastic condition perturbation and progressive weighting to enhance robustness and controllability. During training, both data and conditions are corrupted with Gaussian noise of the same level at random timesteps, and the model learns to predict the added noise. To improve generalization, the condition is randomly dropped with a certain probability (0.1 in the experiments), enabling both conditional and unconditional learning.

During sampling, generation begins from Gaussian noise and proceeds iteratively from the final step to the first. At each step, the condition is perturbed by time-dependent noise and scaled by a dynamic weighting factor. The denoising network progressively refines the sample using the predicted residual noise, yielding reconstructions that flexibly adapt to the conditioning strength while preserving physical consistency.

Algorithm 2 Sampling

Require: Condition y, total timesteps T, parameters $\eta_{\max}, \gamma, w_{\max}, w_{\min}, \sigma$, trained network f_θ

$x_T \sim N(0, I)$, $\epsilon_y \sim N(0, I)$, $z \sim N(0, I)$
for $t = T, T-1, \ldots, 1$ **do**
  $\eta_t \leftarrow \eta_{\max}\left(1 - \frac{t}{T}\right)^\gamma$ ▷ Conditional noise level
  $y_t \leftarrow y + \eta_t \epsilon_y$ ▷ Perturb condition
  $w_t \leftarrow w_{\min} + (w_{\max} - w_{\min})\left(\frac{t}{T}\right)^\sigma$
  $\tilde{y}_t \leftarrow y_t \cdot w_t$ ▷ Weighted condition
  $\hat{\epsilon}_t \leftarrow f_\theta(x_t, t, \tilde{y}_t)$ ▷ Predict noise
  $\mu_\theta(x_t, t, \tilde{y}_t) \leftarrow \frac{\left[x_t - \frac{1-\bar{\alpha}_t}{\sqrt{1-\bar{\alpha}_t}}\hat{\epsilon}_t\right]}{\sqrt{\bar{\alpha}_t}}$ ▷ Denoising step
  if $t > 1$ **then**
    $x_{t-1} \leftarrow \mu_\theta(x_t, t, \tilde{y}_t) + \sigma_t z$
  else
    $x_{t-1} \leftarrow \mu_\theta(x_t, t, \tilde{y}_t)$
  end if
end for
return reconstructed sample x_0

III. Results

The test set was configured with a core diameter of 30 nm, $f_x = 25$ kHz, and $N_d = 99$. Using the low-gradient SM as a conditional input, the corresponding high-gradient version was generated via sampling. As shown in Figure 1, the proposed method effectively generates high-gradient SM, achieving performance closely matching that of the simulated counterparts.

IV. Conclusions

This work presents a diffusion-based method for synthesizing high-gradient SM through progressive condition decay, using low-gradient SM inputs as conditions. The approach effectively reconstructs high-gradient profiles and has been validated through simulations. Future work will extend this method to experimental data acquired from a real MPI scanner, aiming to evaluate its applicability under practical imaging conditions.

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Author's statement

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