Proceedings Article

A Progressive Transformer–GAN Framework for System Matrix Recovery in Magnetic Particle Imaging

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Abstract

Magnetic Particle Imaging (MPI) is an emerging non-invasive high-resolution technique, but its practicality is constrained by time-consuming repetitive calibration of the System Matrix (SM) when parameters, particle types, or environments change. To address this, we propose TP-GAN, a Transformer-based Progressive GAN for MPI SM super-resolution. It integrates a feature enhancement module to stabilize SM's physical structure and capture cross-scale correlations, with multi-loss optimization improving consistency between super-resolution and real high-resolution SM, as well as accuracy and anti-noise performance. Experimental results show TP-GAN outperforms existing methods, reducing reliance on repeated calibration and advancing MPI's biomedical applications.

I. Introduction

Magnetic Particle Imaging (MPI) is a non-invasive molecular imaging technique with exceptional sensitivity and high spatiotemporal resolution, showing great potential in preclinical applications and future clinical theranostics [1].

System Matrix (SM) reconstruction is critical for MPI. Traditional calibration relies on repeated magnetic nanoparticle sample translation and signal averaging, which is time-consuming and impractical when parameters or conditions change [2, 3]. Existing acceleration methods such as compressive sensing and interpolation face limitations in efficiency or quality. Deep learning-based SM super-resolution approaches only focus on simple pixel-level loss and suffer from inefficient low-resolution to high-resolution feature learning under large upsampling factors [3, 4]. To address these issues, this study proposes TP-GAN, a Transformer-based progres-sive GAN for MPI SM super-resolution. It integrates attention feature reinforcement and iterative mapping learning: attention feature reinforcement leverages residual connections and attention mechanisms to stabilize physical structure and capture cross-scale correlations, while iterative mapping learning utilizes GAN's adversarial mechanism and multi-loss collaboration to optimize pixel accuracy[5], physical features, and anti-noise performance. This design overcomes the limitations of existing methods, including inadequate nonlinear mapping modeling, compromised feature consistency, and noise or blurring.

II. Method and materials

In MPI, the relationship between particle concentration $c(\cdot)$ and Fourier coefficients $\hat{u}_k$ of the induced voltage at

frequency f_k is defined by the linear integral equation:

$$\hat{u}_k = \int_\Omega \hat{s}_k(\mathbf{r})c(\mathbf{r})\mathrm{d}^3 r \qquad (1)$$

where $\mathbf{r}$ denotes spatial position, k is the frequency index, and $\hat{s}_k(\cdot)$ is the system function; The main objective of this study is to reconstruct a high-resolution **S** using a subset of the total N sampling positions.

In this study, we frame the SM recovery problem as an image-domain super-resolution task and solve it using TP-GAN, as shown in Figure 1.

Figure 1: The overall framework of the proposed TP-GAN.

The generator maps LR to HR SM by learning their nonlinear relationship: it converts 3-channel RGB input to 32-channel for shallow feature extraction ($\mathbf{u}_0$), then integrates Transformer modules (attention, feedforward), progressive upsampling (two-step with pyramid attention), and a reconstruction module. Residual/skip connections preserve features and enhance information flow, while a convolution layer resizes features to HR dimensions for high-fidelity SM synthesis. The discriminator uses residual connections for stable gradients and AvgPool2d for dimensionality reduction. Convolutional layers with ReLU/LeakyReLU introduce non-linearity, and a sigmoid function outputs real vs. generated SM probability scores—driving the generator to produce $\hat{s}_{HR}$ matching real MPI measurements.

III. Results

Figure 2 shows 3D SM calibration results on the openMPI dataset. Deep learning models (e.g., 3dSMRnet) outperform traditional methods (Trilinear interpolation/CS), which lack utilization of HR SM prior knowledge and yield poor calibration accuracy. Among all methods, TP-GAN achieves optimal SM recovery, with stronger detail/texture restoration, higher consistency with ground truth, and smaller error map values than other deep learning models.

Figure 2: The visualization results and error maps of 3D SMs

IV. Discussion and Conclusion

This study designs TP-GAN, a Transformer-based progressive GAN for MPI SM super-resolution, integrating attention feature reinforcement and iterative mapping learning. The discriminator captures LR-HR image relationships by learning HR SM's texture, detail, and structural characteristics. Experiments show TP-GAN outperforms traditional SM acquisition and state-of-the-art recovery methods in SM estimation and reconstruction quality, enhancing MPI's calibration efficiency and biomedical applicability. Future work will validate its in vivo performance to advance translational value.

Author's statement

Conflict of interest: Authors state no conflict of interest.

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