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CVU-SM: Complex-Valued U-Shaped Network for System Matrix Fast Calibration

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Abstract

Magnetic Particle Imaging (MPI) faces a major bottleneck in the lengthy calibration required for system matrix acquisition. To address this, a complex-valued neural network-based super-resolution framework, CVU-SM, is proposed. Built on a U-shaped encoder-decoder architecture with complex-valued residual-in-residual dense blocks, CVU-SM preserves both magnitude and phase information to accurately reconstruct high-resolution system matrices from low-resolution inputs. Evaluated on the open-source dataset, it outperforms existing deep learning methods in system matrix quality and downstream image reconstruction, demonstrating strong generalization and thereby enabling fast, high-quality MPI calibration.

I. Introduction

Magnetic Particle Imaging (MPI) reconstructs the spatial distribution of superparamagnetic iron oxide nanoparticles (SPIONs) by detecting their magnetization response to an applied alternating magnetic field. Common MPI reconstruction methods include the system matrix (SM) and x-space method. The SM-based method necessitates the utilization of a small sample to traverse the field of view (FOV) for the calibration of the SM. However, the main drawback of this method is the considerably long calibration time. For an SM with 37×37×37 voxels, calibration requires approximately 32 hours [1]. Furthermore, any variations in the characteristics of the tracer or the magnetic field environment dictate the need for recalibrations, thereby exacerbating the challenge. Thus, the pursuit of strategies to reduce the calibration time is one of the most challenging topics in the MPI research field.

Recently, numerous deep learning-based methods have emerged to facilitate this task. For instance, 3d-SMRnet was the first model to employ a convolutional neural network (CNN) for 3D SM calibration [1]. Güngör et al. [2] introduced TranSMS, a hybrid CNN-Transformer architecture for 2D SM calibration, while Shi et al. [3] further enhanced SM calibration by explicitly incorporating coil-channel and frequency-index information into the Transformer architecture. However, these methods overlook the importance of jointly preserving magnitude and phase information in SM super-resolution. To address this, we propose CVU-SM, a complex-valued neural network (CVNN)-based U-shaped encoder-decoder architecture for fast, high-quality SM calibration.

II. Method

We used the OpenMPI dataset [4], acquired on a Bruker preclinical MPI scanner, with 3D Lissajous calibration data over a 37×37×18.5 mm^3 FOV. The training set was built from Experiment 7 (Synomag-D particles), and the test set from Experiment 6 (Perimag particles), both using the same 3D Lissajous sequence. The 3D volumetric SM was segmented into individual 2D slices along dif-

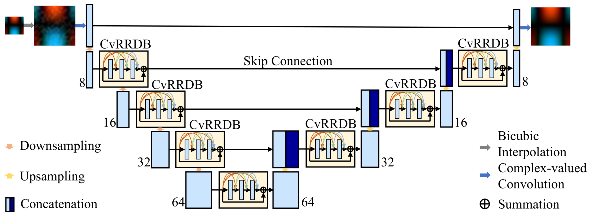

Figure 1: The detailed architecture of the proposed CVU-SM.

ferent heights. In the training set, we only retained SM rows with a signal-to-noise ratio greater than 5, retaining 63502 rows. All slices were cropped to 32×32 and downsampled by averaging to generate low-resolution SMs.

Figure 1 shows the schematic of the proposed CVU-SM framework. CVU-SM is a fully complex-valued super-resolution network with a 4-layer U-shaped encoder-decoder architecture. The core innovation of the network lies in the design of a complex-valued residual-in-residual dense block (CvRRDB) based on complex-valued convolutions and complex-valued activation functions. This architecture more effectively preserves both phase and magnitude information of the input in the complex domain. The encoder gradually expands channels from 8 to 64 while halving spatial resolution at each level to capture multi-scale features. The decoder restores resolution via transposed convolutions and fuses encoder features through skip connections.

During training, the loss function was the weighted sum of mean absolute errors computed separately on the real and imaginary parts. The Adam optimizer coupled with a cosine annealing learning rate scheduler was applied. A batch size of 512 was employed for up to 500 epochs, with an early stopping strategy.

III. Results

We evaluated the proposed framework on both SM super-resolution and MPI image reconstruction against state-of-the-art deep learning methods. Visualizations of the SM images produced by our method are shown in Figure 2(a) and (b), and the results of quantitative evaluation metrics are presented in Table 1. For image reconstruction, we reconstructed three 2D phantoms from an in-house dataset [5] and two 3D phantoms [4] from the OpenMPI dataset, as shown in Figure 2(c) and (d), respectively. Both qualitative and quantitative results confirm that our method achieves higher accuracy, better artifact suppression, and superior generalization than existing approaches.

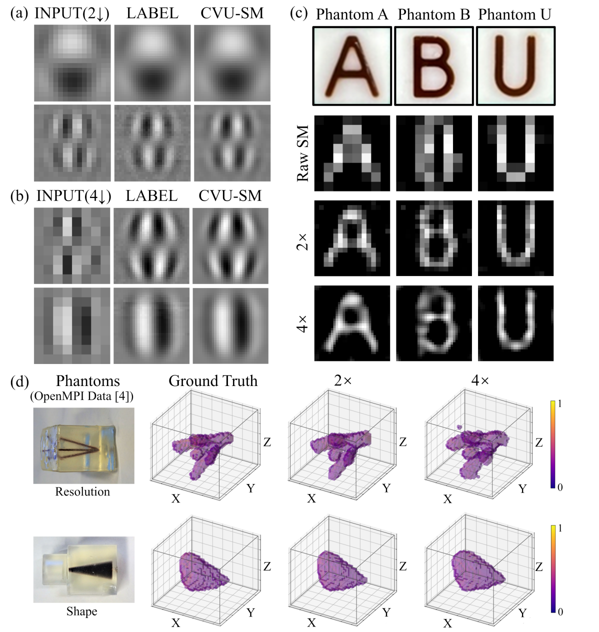

Figure 2: SM row visualizations at 2× (a) and 4× (b) downsampling, and MPI images reconstructed with CVU-SM (c)(d).

Table 1: 2D SM calibration results in OpenMPI dataset.

Methods	2×		4×		8×	
	nRMSE	SSIM	nRMSE	SSIM	nRMSE	SSIM
Bicubic	2.79%	0.9770	10.53%	0.8594	47.11%	0.4026
SRCNN [6]	2.38%	0.9803	7.49%	0.9236	44.40%	0.5010
FSRCNN [7]	2.38%	0.9809	6.34%	0.9421	41.68%	0.5798
ESPCN [8]	2.39%	0.9809	6.70%	0.9366	42.41%	0.5388
SMRNet [1]	2.35%	0.9812	5.37%	0.9549	40.22%	0.6336
TransSMS [2]	2.34%	0.9809	5.25%	0.9550	36.90%	0.6721
CVU-SM	**2.31%**	**0.9814**	**5.10%**	**0.9573**	**35.69%**	**0.7066**

IV. Conclusion

We propose CVU-SM, a complex-valued super-resolution framework for fast and accurate MPI SM calibration. Built on a fully complex U-shaped encoder-decoder with complex residual-in-residual dense blocks, it effectively preserves magnitude and phase information of the SM. Results show that CVU-SM outperforms state-of-the-art methods in both SM super-resolution and downstream MPI image reconstruction, offering a promising, generalizable solution that reduces calibration time while maintaining high image quality.

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Author's statement

Conflict of interest: Authors state no conflict of interest.

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