International Journal on Magnetic Particle Imaging
Vol 11, No 1, Suppl 1, Article ID 2503047, 2 Pages

Proceedings Article

Denoising the system matrix with deep neural networks for better MPI reconstructions

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Abstract

Magnetic Particle Imaging commonly relies on the system matrix (SM) to reconstruct particle distributions, but noise during acquisition limits both its resolution and image quality. Traditionally, noise reduction requires averaging multiple measurements, which increases acquisition time. This paper presents a deep neural network trained on simulated SMs and measured background noise, which effectively generalizes to real-world data. The model recovers higher frequency components of the SM and serves as a general pre-processing step, enhancing image reconstruction quality while reducing the need for extensive averaging, thus accelerating SM acquisition.

I. Introduction

In Magnetic Particle Imaging (MPI) reconstruction, estimating the particle distribution represents a linear inverse problem. The integral kernel, defined by the scanner and particle parameters, is referred to as the system matrix (SM). While the SM can be modeled [1], it is usually measured by moving a small delta sample on a grid.

Noise in MPI systems is complex in nature [2] and limits the resolution of the SM. [3]. To reduce noise, multiple measurements are averaged which extends the acquisition time. The thresholded discrete cosine transform can be employed to denoise SM frequency components [4]. Recently, deep neural networks (DNNs) have been proposed to denoise measured MPI signals [5] and reconstructions [6]. However, forming a training dataset is challenging, as the ground truth (GT) is not available, and the noise model cannot be precisely modeled.

In this paper, we train a DNN for SM denoising using modeled SMs and measured background signals. The model generalizes well to real data, improves image quality and allows for shortening the calibration time.

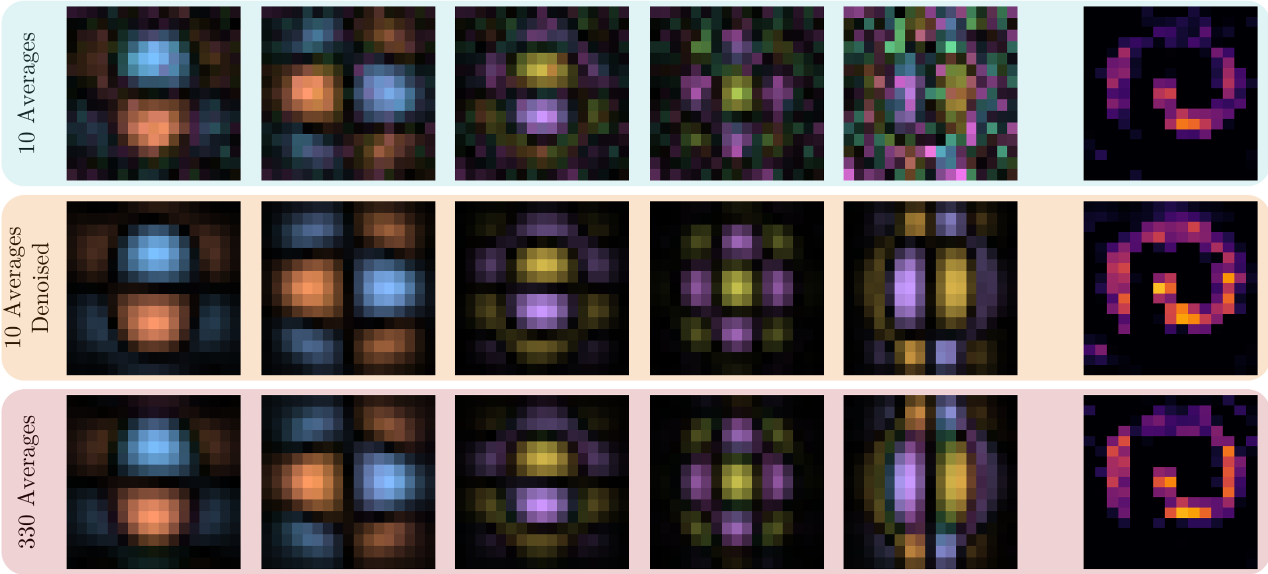
II. Methods and Materials

We consider a pre-clinical MPI system from Bruker (Ettlingen, Germany). Measurements were performed using a 2D Lissajous sequence with fluid perimag particles. The SM was measured repeatedly 10 and 330 times.

We consider a 2D denoising problem of complex-valued frequency components of the SM. A noise-free SM is generated by solving the Fokker-Planck equation for Néel rotation[1] and then split randomly into training and test sets in a 9:1 ratio. To simulate noisy SMs, a long sequence of background noise measurements is normalized to zero mean, randomly sub-sampled, and reshaped to match the dimensions of the SM. Both the noise and the frequency components are scaled to their respective maximum values, and the noise is randomly re-scaled to simulate different SNRs.

We train a 17-layer bias-free DnCnn [7] model by minimizing the residual MSE with the Adam solver (learning

[1] The implementation was taken from https://github.com/IBIResearch/EquilibriumModelWithAnisotropy



(a) Frequency components (b) Reconstructions

Figure 1: Frequency components of the SMs (a) with the corresponding reconstructions of the snake phantom (b). The rows correspond to different SMs: with 10 averages, denoised after 10 averages, and 330 averages. The components correspond to 101, 103, 153, 176, 149 kHz.

rate: $3 \cdot 10^{-4}$, number of epochs: 10^4). Complex-valued components are considered as two-channel real images. The trained model is then applied to the measured SM with 10 averages.

To assess the impact of denoising, a snake phantom measurement [1] (1000 averages) was pre-processsed (SNR threshold: 1.5, background subtraction) and reconstructed using the Kaczmarz method with Tikhonov regularization ($\lambda = 0.3$) and row-normalized SMs.

III. Results

Figure 1 shows denoising results for several components of the measured SM with 10 averages. The components are visually recovered compared to the SM with 330 averages. The reconstruction with the denoised SM demonstrates improved contrast and the recovery of the upper part of the snake. It also shows a minor blurring compared to the reconstruction using the SM with 330 averages and amplifies an artifact in the lower left corner.

IV. Discussion and Conclusion

We demonstrated that a DNN trained on simulated data can effectively generalize to measured SMs. The developed model serves as a general pre-processing step, enhancing the SNR for SMs with varying numbers of averages. Our results highlight the model's potential to reduce the required number of averages in SM measurements, with the primary impact being the recovery of bias and contrast. Future research should extend the approach to 3D SMs, which would require computationally more efficient simulation models [1].

Author's statement

This project is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – SFB 1615 – 503850735. Authors state no conflict of interest.

References

[1] M. Maass *et al.* Equilibrium model with anisotropy for model-based reconstruction in magnetic particle imaging. *arXiv preprint arXiv:2403.00602*, 2024.

[2] H. Paysen *et al.* Characterization of noise and background signals in a magnetic particle imaging system. *Physics in Medicine & Biology*, 65(23):235031, 2020, doi:10.1088/1361-6560/abc364.

[3] T. Knopp *et al.*, Limitations of measurement-based system functions in magnetic particle imaging, in *Medical Imaging 2010: Biomedical Applications in Molecular, Structural, and Functional Imaging*, 7626, 427–434, SPIE, 2010. doi:10.1117/12.844181.

[4] A. Weber *et al.* Reconstruction Enhancement by Denoising the Magnetic Particle Imaging System Matrix Using Frequency Domain Filter. *IEEE Transactions on Magnetics*, 51(2):1–5, 2015, doi:10.1109/TMAG.2014.2332612.

[5] H. Peng *et al.* Multi-scale dual domain network for nonlinear magnetization signal filtering in magnetic particle imaging. *Biomedical Signal Processing and Control*, 85:104863, 2023, doi:10.1016/j.bspc.2023.104863.

[6] H. Peng *et al.* Self-supervised signal denoising in magnetic particle imaging. *IJMPI*, 9(1 Suppl 1), 2023, doi:10.18416/IJMPI.2023.2303039.

[7] S. Mohan *et al.*, Robust and interpretable blind image denoising via bias-free convolutional neural networks, 2020.

