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A correlation-constrained SNR frequency selection algorithm for magnetic particle imaging reconstruction

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Abstract

System matrix-based reconstruction is a commonly used method in magnetic particle imaging (MPI). However, due to the large memory requirements, lengthy processing times, and ill-posed nature of the system matrix, computational feasibility remains limited to perform reconstruction using the entire matrix. The most common approach involves frequency component selection based on signal-to-noise ratio (SNR), where a limited number of frequency components are chosen for reconstruction. However, selection based solely on SNR risks discarding critical image information, and frequency components with high SNR may exhibit redundant information. Therefore, this paper proposes a dual-criterion frequency selection strategy based on the synergistic integration of correlation constraints and SNR ranking. It aims to supersede naive SNR selection by jointly optimizing the condition number of the system matrix, which can ensure the reconstructed image's SNR while prioritizing mutually independent components to better recover image details. Experimental results on real data demonstrate that the proposed algorithm demonstrates superior reconstruction fidelity.

I. Introduction

Magnetic particle imaging (MPI) is an emerging tomographic imaging technique that has gained prominence in recent years [1]. It offers advantages such as high resolution, no imaging depth limitations, and the absence of ionizing radiation, presenting excellent prospects for clinical applications [2].

System matrix reconstruction faces ill-posed challenges necessitating frequency selection[3]. Therefore, pre-reconstruction frequency component selection is essential. Traditional signal-to-noise ratio (SNR) methods predominantly select low-frequency signals with high SNR[4]. However, critical reconstruction information is often embedded in high-frequency components. To resolve this, we propose a correlation-constrained SNR algorithm selecting high SNR components while enforcing independence via cosine similarity. Evaluated against SNR and gravitational search algorithm (GSA) methods on openMPI data [5,6], our approach achieves superior reconstruction fidelity.

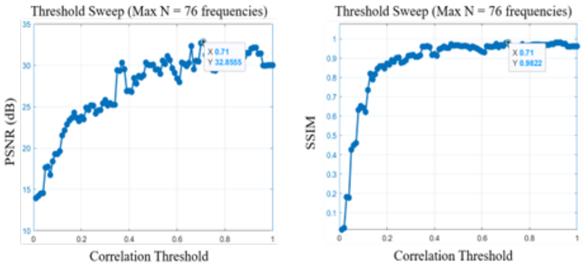

Figure 1: PSNR and SSIM curve diagrams during parameter threshold iteration process of our method.

Table 1: The three metrics results of the experiment

	Data	Train	Test	
Param	Phantom	shape	resolution	concentration
PSNR	SNR(5%)	30.0228	25.1893	30.0178
	GSA(5%)	39.0999	22.9096	26.2625
	Ours(5%)	32.8555	29.0873	33.7605
SSIM	SNR(5%)	0.9623	0.8351	0.8705
	GSA(5%)	0.9953	0.6782	0.6529
	Ours(5%)	0.9822	0.9464	0.9388
NRMSE	SNR(5%)	0.0311	0.0550	0.0236
	GSA(5%)	0.0153	0.0638	0.0293
	Ours(5%)	0.0218	0.0351	0.0158

II. Methods and materials

II.I. Correlation-constrained SNR frequency selection algorithm

When selecting frequency components for reconstruction, high similarity between system matrix frequency components indicates information redundancy. Using such components provides negligible quality improvement while increasing computation complexity. To ensure independence among selected frequency components, we introduce a correlation constraint.

Our algorithm first calculates the SNR for each frequency component using the following formula:

$$SNR(f_i) = \frac{\sqrt{(S^{\delta}_{1,f_i})^2 + (S^{\delta}_{2,f_i})^2 + \ldots + (S^{\delta}_{N,f_i})^2}}{\sqrt{(S^{0}_{1,f_i})^2 + (S^{0}_{2,f_i})^2 + \ldots + (S^{0}_{N,f_i})^2}} \tag{1}$$

where $i = 1, 2, \cdots, M$, S^{δ} and S^{0} are derived from the frequency spectra of the calibration signals measured with and without the sample probe, with N representing the number of calibration points. Set a correlation threshold to ensure that the correlation value of each frequency component in the selected set of frequency components satisfies the following condition:

$$\max_{v \in \text{Selected set}} \left(\frac{|v_{ws}^{H} v|}{\|v_{ws}\|_2 \|v\|_2} \right) < \text{corr threshold} \tag{2}$$

where v denotes the set of frequency components that have already been selected, while v_{ws} represents the frequency components that have not yet been selected.

We selected the frequency component with the highest SNR as the first chosen frequency. Subsequently, frequency candidates were traversed in descending order of SNR. Each candidate frequency was evaluated against the already selected frequencies using eq. (2) to compute the correlation. If the correlation fell below a given threshold, the frequency was selected; otherwise, it was skipped.

Conducting two-dimensional slicing experiments on publicly available openMPI data. The system matrix comprises a total of 817 frequency components per channel across two channels, yielding a combined total of 1634 components. After applying an 80 Hz high-pass filter, this number was reduced to 1528 components. We ultimately selected 76 frequency components for reconstruction.

In our experiments, the SNR-based algorithm and the GSA algorithm were selected as comparison methods. The GSA algorithm is a data-driven meta-heuristic optimization technique that iteratively searches for the optimal frequency subset by simulating gravitational interactions to minimize the reconstruction error of a specific training phantom. The specific parameters of the GSA algorithm are set as follows: The parameters for the GSA were set consistent with the optimized configuration reported in our previous work [6]. The specific parameters used were: initial gravitational constant $G_0 = 100$, decay constant $\alpha = 20$, population size $N = 50$, and maximum iterations $T = 500$.

III. Experiments and results

Performance was evaluated on three openMPI phantom datasets for 2D MPI reconstruction. Using "shape" for frequency selection calibration, "resolution" and "concentration" for generalization testing, we compared against SNR and GSA methods. All reconstructions used Kaczmarz algorithm with iteration number $I = 10$ and regularization parameter $\alpha = 0.001$. PSNR, SSIM and NRMSR metrics were computed against full frequency reference in Table 1.

Threshold optimization experiments revealed an optimal correlation threshold of 0.71, as demonstrated in Figure 1. In practical experiments, iterative threshold adjustment is performed for different datasets to ensure an optimal threshold is obtained for each data type.

Figure 2 demonstrates the reconstructed images of the three methods. The performance discrepancy of the GSA algorithm between the training and test sets primarily stems from overfitting and its frequency-specific bias toward particular phantoms. As a heuristic optimization algorithm, GSA aims to minimize the reconstruction

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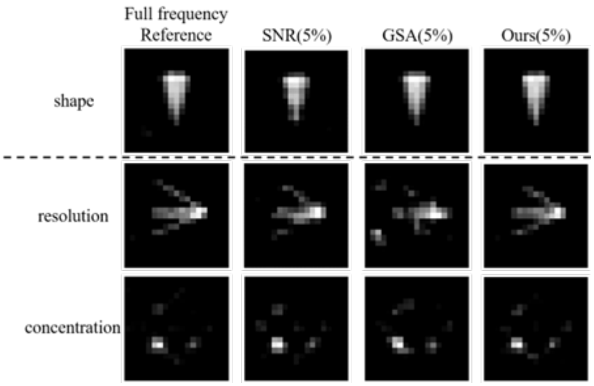

Figure 2: The reconstructed images of the SNR, GSA and our algorithm.

error of the training phantom. Consequently, it tends to search for and lock onto a set of frequency components that perfectly represent the specific geometry used during training. This results in a selected frequency subset that is highly specific to the spatial features of the training data. However, the energy distribution in the frequency domain varies across objects with different geometric structures. The optimal frequency subset for the shape phantom often lacks key frequency components necessary for accurately reconstructing the resolution or concentration phantoms.

In contrast, our proposed method selects frequencies based on the physical properties and mathematical properties of the system matrix itself. These properties reflect the intrinsic characteristics of the MPI imaging system rather than features of any specific object under test. Therefore, our approach demonstrates stronger robustness and better generalization capability when applied to previously unseen objects.

IV. Conclusions

This work resolves key limitations of SNR frequency selection by introducing a correlation constrained algorithm. Building on high SNR component selection, it incorporates cosine similarity constraints to eliminate redundant frequencies and preserve critical image details. Validated on public MPI datasets, the method enables efficient, high-quality reconstructions with significant clinical potential. While full-frequency reconstruction served as the reference baseline in our experiments, it is important to note that retaining all frequencies in practical MPI applications often introduces high-frequency noise, which can degrade the visual quality of the reconstructed images. Therefore, defining a more robust and clinically meaningful ground truth remains an important open question for future research.

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Author's statement

Authors state no conflict of interest.

References

[1] B. Gleich and J. Weizenecker, "Tomographic imaging using the nonlinear response of magnetic particles," Nature, vol. 435, no. 7046, pp. 1214–1217, Jun. 2005.

[2] Kumar PPP. Magnetic Particle Imaging in Oncology: Advances and Prospects for Tumor Progression Monitoring and Targeted Therapy. Published online September 3, 2025. doi:10.20944/preprints202509.0352.v1

[3] Shan S, Zhang C, Cheng M, et al. SPFS: SNR peak-based frequency selection method to alleviate resolution degradation in MPI real-time imaging. Physics in Medicine and Biology. 2024;69(11):115028. doi:10.1088/1361-6560/ad3c90

[4] Sun S, Sun S, Wang Y, et al. A cost-effective magnetic particle imaging scanner based on mixing-frequency spectra. Measurement. 2026;257:118595. doi:10.1016/j.measurement.2025.118595

[5] T. Knopp et al., "openMPI: An open-source raw data format for magnetic particle imaging," Int. J. Magn. Part. Imag., vol. 6, no. 2, 2020.

[6] W. Jiang et al., "Frequency components selected based on gravitational search algorithm for magnetic particle imaging reconstruction," Int. J. Magn. Part. Imag., vol. 10, no. 1 (Suppl. 1), p. 2403005, 2024.

10.18416/ijmpi.2026.2603029