

### Proceedings Article

# Fusion of overlapping patches in x-Space MPI

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#### Abstract

In x-space reconstruction of magnetic particle imaging (MPI) data, the information lost due to filtering for trajectories with 1D drive field (DF) was shown to be a DC term, which can be recovered by enforcing image non-negativity and smoothness. However, for trajectories with multi-dimensional DFs, such as the Lissajous trajectory, the loss is no longer constant throughout a patch. These space-variant losses engender artifacts in the aftermath of fusion. In this work, we present a fusion method for overlapping patches in x-space reconstruction that can handle these losses. This method first compensates for image loss due to filtering, followed by a fusion that places a higher emphasis on the patch where the Lissajous trajectory had a closer-to-orthogonal intersection, ensuring near-isotropic effective point spread function (PSF) throughout the fused image.

## I Introduction

X-space reconstruction of magnetic particle imaging (MPI) data typically utilizes linear scanning trajectories [1-2]. Recently, we have proposed a fully automated gridding reconstruction for non-Cartesian x-space MPI, extending x-space reconstruction to more complex multidimensional trajectories [3]. This technique was demonstrated for a single patch. In the case of multiple overlapping patches, however, fusing images from these patches requires careful consideration [4-5]. This is because a point in the overlapping region may attain different intensities in the x-space images from different patches. There can be two different causes behind these discrepancies. First, a point may be scanned in different directions in different patches, resulting in inconsistent blurring among patches. Second, a point may experience different losses in different patches due to direct feedthrough filtering. For trajectories with 1D drive field (DF), the information lost due to filtering was shown to be a DC term, and a reconstruction that enforces image non-negativity and smoothness was proposed to recover

the lost DC terms [6]. However, for trajectories with multidimensional DFs, such as the Lissajous trajectory, the loss is no longer constant throughout a patch.

In this work, we propose a fusion method for overlapping patches in x-space reconstruction. First, images from each patch are compensated for the loss due to filtering by exploiting the information from the overlapping regions. Next, when fusing the compensated images at a given point, the proposed technique places a higher emphasis on the patch where the Lissajous trajectory had a closer-to-orthogonal intersection, ensuring nearisotropic effective point spread function (PSF) throughout the fused image [3,7]. With simulation results, we demonstrate that the proposed fusion technique can reconstruct images with significantly reduced artifacts.

## II Material and methods

Suggested pipeline consists of image compensation and image fusion stages. In the compensation part, the over-



**Figure 1:** The contribution maps for the left and right image over the overlapping region *X*. A higher map intensity correspond to a larger contribution from the corresponding image at that pixel in the fused image.



**Figure 2:** (a)  $1.2x2 \text{ cm}_2$  Phantom, (b) left patch with size 1.2x1.2 cm<sub>2</sub>, (c) right patch with size  $1.2x1.2 \text{ cm}_2$ .

lapping region redundancy is utilized for compensation, which prepares the data for fusion.

#### **II.I Image Compensation**

An image in x-space MPI is formed by normalizing the filtered collinear signal  $s_{\parallel}(t)$  by the speed of the field free point (FFP)  $||\dot{x}_s||_2$  [1-2]:

$$IMG_{||}(x_{s}(t)) = s_{||}(t)/||\dot{x}_{s}||_{2}$$
(1)

This image is sampled at instances  $t_k$  and placed at non-Cartesian FFP locations  $x_s(t_k)$ . Next, a gridding algorithm *G* can be used to generate a consistent x-space image out of these samples via  $IMG(x) = G\{IMG_{||}(x_s(t_k))\}$ [3].

MPI signal is concentrated at the harmonics of the drive field frequencies. The lost information due to filtering can be approximated as the summation of the responses at discrete frequencies near the fundamental harmonic. Using this fact that, we form a dictionary of images that describes the contribution of each discrete frequency. Accordingly, the image contribution due to a discretized frequency  $f_l$  can be expressed as:

$$I\hat{M}G(x_{s}(t), f_{l}) \triangleq e^{j2\pi f_{l}t} / ||\dot{x}_{s}||_{2}$$
(2)

After sampling and gridding by G, a dictionary for the image space is generated:

$$D \triangleq \{ v_{f_l} \triangleq G\{ I \hat{M} G_{\parallel}(x_s(t_k), f_l) \}(x) \}.$$
(3)



**Figure 3:** Left patch (a) without and (b) with direct feedthrough filtering, and (c) the corresponding loss. Right patch (d) without and (e) with direct feedthrough filtering, and (f) the corresponding loss.

Here,  $v_{f_l}(x)$  is the gridded image pattern corresponding to  $f_l$ . In this work, for two overlapping images  $IMG_1(x)$ ,  $IMG_2(x)$  with overlap region X and intersection points  $x_k$ , the following minimization problem is solved:

$$\underset{\alpha_{1},\dots,N,\beta_{1}\dots,N}{\operatorname{argmin}} \sum_{x_{k}\in X} w_{k} \left( \left( IMG_{1}(x_{k}) + \sum_{i=1}^{N} \alpha_{i} v_{f_{i}}(x_{k}) \right) - \left( IMG_{2}(x_{k}) + \sum_{i=1}^{N} \beta_{i} v_{f_{i}}(x_{k}) \right) \right)^{2}$$
(4)

Here,  $f_{1...N}$  is the set of frequencies in the lost band and  $w_k$  are the "orthogonality weights" for the intersection points  $x_k$ . A step function of the intersection angle of the Lissajous trajectory at position  $x_k$  was used to compute these weights, as orthogonal intersection positions of the Lissajous trajectory have near-isotropic effective PSFs [3]. The solution to Eq. 4 reveals optimal combination of response images, which when added to the filtered image, minimizes the squared error in the overlap region X.

### II.II Image fusion

A naïve way of fusing images could be assigning equal contributions to both images in the overlap region X. However, the two images are not equally reliable at each pixel in X. As an improvement, the contribution of an image to a pixel may be made to decay with its distance under varying regimes (linear,  $\sin^2$ ) as suggested in [3-4]. In this work, the orthogonality of the Lissajous trajectory intersections at a given pixel is utilized as the reliability metric. By interpolating the angles of intersections over the entire FOV, each image is assigned an orthogonality score at every pixel. The contributions of images at a particular pixel is then taken to be the soft-max distribution over the orthogonality scores of images at that pixel. For two overlapping patches, Fig. 1 shows the corresponding weights to be used in image fusion.



**Figure 4:** Fusion of unfiltered patches with (a) equal contributions and (b) soft-max contributions. Fusion of filtered patches without image compensation, with (c) equal contributions and (d) soft-max contributions. Fusion of image compensated filtered patches with (e) equal contributions and (f) the proposed soft-max contributions.

#### **II.III Simulations**

Simulation were performed in MATLAB with a custom MPI toolbox. The selection field gradients were (3, 3, -6) T/m along (x,y,z) directions, and nanoparticles with 25nm diameter were assumed. The 1.2x2 cm<sup>2</sup> phantom shown in Fig. 2 was used. Two 1.2x1.2 cm<sup>2</sup> patches overlapping over a 1.2x0.4 cm<sup>2</sup> region were scanned using a 2D Lissajous trajectory in x-y plane, with  $f_0 = 25$  kHz and  $N_p = 99$ . A high-pass filter with 45 kHz cut-off frequency was used for direct feedthrough filtering.

### **III** Results and discussion

Figure 3 shows the left and right patches, and their image losses due to direct feedthrough filtering. These losses are not constant throughout the patches, and hence cannot be fixed with DC loss compensation.

Figure 4 shows the improvements achieved by the proposed image compensation and image fusion techniques. A comparison between left and right columns reveals that the unnatural transition regions in the equalcontribution case (red arrows) are solved via the fusion with the proposed soft-max contributions. Image fusion without compensation leaves behind artifacts in the overlapping region, even when soft-max contributions are utilized (yellow arrow). As shown in Fig. 4f, This problem is alleviated by the proposed image compensation followed by fusion with soft-max contributions.

### **IV** Conclusions

In this work, a fusion method for overlapping patches in x-space reconstruction is presented. Weighting each image with soft-max contributions yield significantly improved results, while image compensation for the lost fundamental frequency alleviates remaining image artifacts.

### Author's Statement

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