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Eigen-reconstructions: a closer look into the System Matrix

J. Chacon-Caldera[1,*] · H. Lehr[1] · K. Sajjamark[1] · J. Franke[1]

[1]Bruker BioSpin MRI GmbH, Ettlingen, Germany
[*]Corresponding author, email: Jorge.Chacon-Caldera@Bruker.com

Abstract

Magnetic particle imaging (MPI) offers an exceptional set of advantages compared to other imaging modalities including high sampling efficiency and sub-millimeter spatial resolution. From these two, the former is maximized during the data acquisition using non-cartesian sampling trajectories while the latter relies on the compensation of the point spread function of the system and the superparamagnetic iron oxide particles (SPIOs) necessary to generate the MPI signal. The System Matrix (SM) approach for image reconstruction uses a pre-calibration measurement and achieves both purposes simultaneously, relating the concentration of SPIOs and the true particle response to the measured signal. Therefore, the reconstruction will be largely influenced by the quality of the SM besides the measured image data. Moreover, considering the multitude of factors involved in the quality of the reconstructed image, it is difficult to identify sources of image artifacts. In this work, we demonstrate the potential to use reconstructions of individual measurements within the SM (eigen-reconstruction) as a test for both SM and reconstruction quality. We also present an iterative algorithm to enhance image quality (deblur) using eigen-reconstructions.

I Introduction

Magnetic particle imaging (MPI) continues establishing itself as a powerful modality due to its set of remarkable advantages such as high sampling efficiency and sub-millimeter spatial resolution. In terms of sampling efficiency, Lissajous trajectories have enabled the acquisition of whole 3D volumes in e.g. ~21 milliseconds [1]. These trajectories often sample the volumes using variable densities and velocities depending on spatial location. Additionally, the superparamagnetic iron oxide particles (SPIOs), necessary to generate the MPI signal, add uncertainty to the MPI measurements. Their responses during a scan are multifactorial and difficult to predict. Moreover, these responses expand the point spread function, thus limiting the spatial resolution. Due to these factors, the image reconstruction is not trivial. One solution employed for reconstructions is the use of a pre-calibration measurement to characterize the system. This process uses a small delta-type sample scanned at several discrete spatial locations, yielding the so-called System Matrix (SM). This is a measured transfer function that relates the measurement (image) to the object (local SPIO concentration) [2]. Thereby, an image or a volume can be reconstructed using linear algebra techniques such as the Kaczmarz algorithm [3]. This approach is not only robust, but also compensates for uneven sample densities and velocities as well as for the SPIOs' responses which translates to more homogeneous and higher resolution images. Consequently, the reconstructed image strongly depends on the SM's quality which is normally only assessed in Fourier space [4].

Ideally, each measurement composing the SM represents a unique point in space and should be reconstructed as a single voxel with 100 % intensity within the field-of-view (FoV) covered by the trajectory. This

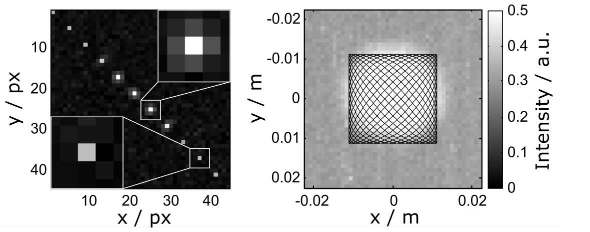

Figure 1: Two representations of eigen-reconstructions (i = 1, $\lambda = 0$). Left: Sum of selected sample positions showing blurring surrounding the center points. Right: Maximum intensity pixel of every sample position showing higher intensities within the area of the Lissajous trajectory with respect to the oversampling area.

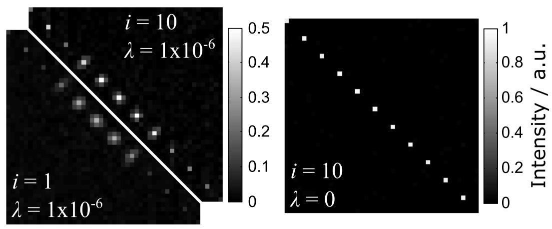

Figure 2: Eigen-reconstructions with different reconstruction parameters.

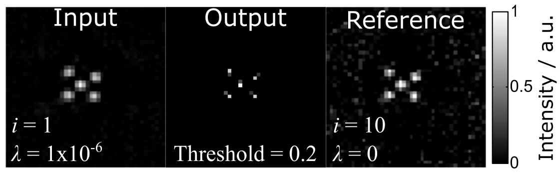

Figure 3: Results from the proposed correction algorithm compared to two different reconstructions.

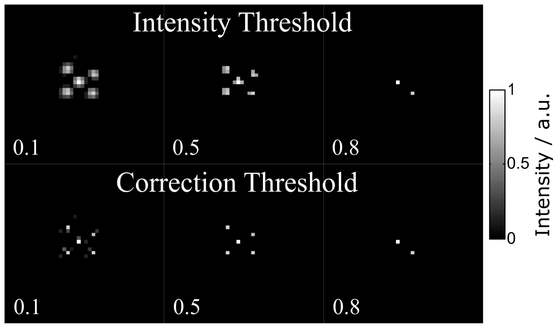

Figure 4: Applying an intensity Threshold on a reconstructed image was not equivalent to correcting with the proposed algorithm using different Thresholds.

should be achieved perfectly if the evaluated data has a perfect match of signal and noise in the SM e.g. when using the own SM measurements as image data. Deviations thereof represent ill-conditions during reconstruction, translating to artifacts in the reconstructed images. In this work, we test this hypothesis by taking sample delta position measurements from the SM and reconstructing them as test images. Thus, performing *eigen-reconstructions* of the SM. We test varying reconstruction parameters and identify cases where artifacts are present as blurring. We then present an algorithm to reduce it using information from the eigen-reconstructions.

II Material and methods

Eigen-reconstructions were performed on MPI measurements available online from the project "open MPI data" [5]. The acquisition parameters of the SM were as follows: tracer: 1 μL (0.5 mol/L) Ferucarbotran (Resovist, Bayer Pharma AG, Berlin, Germany), scanner: free-field point-based preclinical MPI system (Bruker BioSpin MRI GmbH, Ettlingen, Germany). The acquisition parameters were: 2D Lissajous (sine frequencies x = 2.5 MHz/102, y = 2.5 MHz/96) excitation with drive field (DF) amplitude = 14 mT, gradient strength (x- = y-direction) = 1.25 T/m, averages = 1500, bandwidth = 1.25 MHz. The SM was acquired at 1936 spatial locations using a robot for positioning (44x44 point grid) with FoV = 44x44 mm^2 (FoVDF = 22x22 mm^2). Reconstruction was performed using x- and y- receive channels with an 80 kHz high-pass filter. Positive and real signals were enforced.

We proposed a blurring correction algorithm for image data using eigen-reconstructions following these steps: 1) reconstruct an image with any parameters (input), 2) find maximum intensity pixel of that image (I_{MAX}), 3) eigen-reconstruct the corresponding location of I_{MAX} in the SM using the same reconstruction parameters as the image (ISM), 4) correct intensity (I_{MAX} / I_{SM}) and store as output, 5) update input using: input - I_{SM}, 6) iterate while IMAX > Threshold. Due to the subtraction in 5), subsequent iterations loop over high intensity pixels elsewhere in the FoV. The algorithm was tested on the measurement (500 averages) of a 5-point phantom filled with Resovist (point diameter = 1.1 mm, c = 0.5 mol/l) and compared to standard reconstructions [5]. The Threshold value during the correction was modified to show its effect on the output image and to prove that the resulting image is not merely equivalent to applying an intensity threshold on the reconstructed images.

III Results and discussion

In the first eigen-reconstruction, selected measurements in the SM corresponding to different spatially located points along the FoV were individually reconstructed. The sum of each reconstruction using 1 iteration ($i = 1$) and no regularization ($\lambda = 0$) showed increased blurring with higher signal intensity in the central points (Fig. 1, Left). The maximum intensity pixel in each of the eigen-reconstructions (all measurements) showed higher signal in the area covered by the trajectory vs. outside (mean ± standard deviation): 0.44 ± 0.08 vs. 0.31 ± .01 (Fig. 1, Right). The intensities being below 1, represented a reconstruction artifact. Moreover, while, it is known that signals can be detected beyond the area covered by the trajectory [6], the ability to reconstruct the sample in these areas could be due to the perfect noise match (instead of signal) between the measurement and the SM.

In Fig. 2, different parameters showed decreased blurring using a lower λ while the signal converged to the expected value of 1 as i increased. A virtually ideal reconstruction was achieved when optimizing these factors, demonstrating a potential use of the eigen-reconstructions.

The resulting deblurred image from the proposed correction algorithm using test data from the phantom can be observed in Fig. 3. As a comparison, the reference image showed decreased blur compared to the input at the expense of increased noise. On the other hand, our algorithm filtered out the noise.

Finally, evidence is provided in Fig. 4 that the correction algorithm is not equivalent to an intensity threshold. It can be also observed that the objects are well resolved across a wide range of threshold values (0.1-0.5). The evaluation of the effect and efficiency of the correction algorithm using other test data, especially containing more complicated structures with a mix of different concentrations is in the scope of our future work.

IV Conclusions

Regardless of the tested data in the eigen-reconstructions having exact matches with measurements in the SM, some reconstruction parameters yielded output images with inhomogeneous intensities and blurring. Both issues were diminished with parameter optimization. Thus, the potential use of eigen-reconstructions was demonstrated as a testing tool during the reconstruction process. Moreover, these image artifacts present in the eigen-reconstructions are also expected in the test data. Our proposed algorithm decreased blurring, which suggests that the blur in the SM correlate with the blur of the image data and it can be compensated. We expect the use of eigen-reconstructions to be adopted and used routinely as additional tool to ensure SM and reconstruction quality, and to potentially compensate for added blur during the reconstruction.

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