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Multi-Contrast MPI Matrix Compression

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Abstract

Multi-contrast magnetic particle imaging (MPI) reconstructs the signal from different tracer materials or environments, resulting in multi-channel images that enable temperature or viscosity quantification. Since the multi-contrast problem is ill-posed, it is addressed by regularization methods that are commonly solved using the Kaczmarz algorithm. Unlike the single-contrast MPI problem, the multi-contrast one requires a high number of iterations to converge. Matrix compression techniques were already successfully used in single-contrast reconstruction and matrix recovery applications as in compressed sensing. Our work proposes to use matrix compression to reduce the reconstruction time needed to achieve good reconstruction quality in multi-contrast MPI.

I. Introduction

MPI is an emerging medical imaging technique that employs static and dynamic magnetic fields to enable sensitive and fast imaging of magnetic nanoparticles [1]. Multi-contrast MPI enables separate reconstruction of the signal from different tracer materials or environments, which results in multi-channel images presenting different tracer or environment properties, such as temperature [2], viscosity [3], or core size [4].

Multi-contrast MPI reconstruction is quite challenging due to the difficulty of correctly separating the signal into the different channels. This commonly leads to a high number of Kaczmarz iterations to obtain a good channel separation. For instance, in [3, 4], up to 10 000 iterations were required. In MPI, matrix compression techniques were introduced before for both reconstruction convergence improvement [5] and compressed sensing applications [6] considering single-contrast only so far. This work proposes the application of matrix compression [5, 7] for multi-contrast problems to speed up the convergence of reconstruction and reduce memory consumption while maintaining the image quality.

II. Methods and materials

To apply matrix compression, a unitary basis transformation $\boldsymbol{B}$ is applied to the rows of the system matrix $\boldsymbol{S}_l, l = 1, ..., L$. The transformed matrix $\boldsymbol{S}_l \boldsymbol{B}^{\mathsf{H}}$ is then sparsified by applying a threshold and only storing the nonzero entries of the matrix. For multi-contrast MPI, the compression threshold can be chosen individually for each channel. Matrix compression technique is applied to the multi-channel reconstruction as follows

$$\begin{pmatrix} \boldsymbol{S}_1 \boldsymbol{B}^{\mathsf{H}} & \dots & \boldsymbol{S}_L \boldsymbol{B}^{\mathsf{H}} \end{pmatrix} \begin{pmatrix} \boldsymbol{B} c_1 \\ \vdots \\ \boldsymbol{B} c_L \end{pmatrix} = \boldsymbol{u}. \qquad (1)$$

The discrete cosine transform (DCT) is used as basis transformation in this work. For thresholding, we consider the row-wise approach discussed in [8].

Synthetic data derived from measured system matrices of catheter tracking in a vessel with a stenosis scenario is considered for evaluation. The following forward model is used to create the simulated data

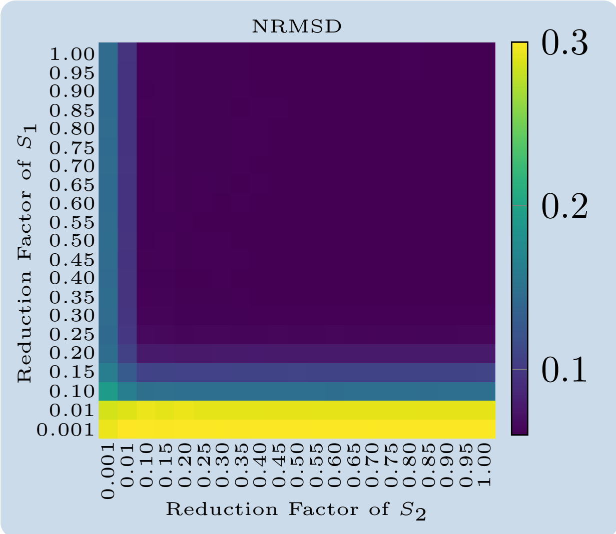

Figure 1: The heatmap shows the NRMSD of the reconstruction results using matrix compression versus the reduction factor for each channel system matrix.

$$\underbrace{\begin{pmatrix} \boldsymbol{S}_1 & \boldsymbol{S}_2 \end{pmatrix}}_{\boldsymbol{S}} \underbrace{\begin{pmatrix} \boldsymbol{c}_1 \\ \boldsymbol{c}_2 \end{pmatrix}}_{\boldsymbol{c}} + \boldsymbol{n} = \boldsymbol{u},$$

where $\boldsymbol{S}$ is the system matrix that consists of the mobilized $\boldsymbol{S}_1$ and immobilized $\boldsymbol{S}_2$ system matrices acquired for the two channels, $\boldsymbol{u}$ is the measurement vector, and $\boldsymbol{n}$ is synthetic white Gaussian noise with variance 0.5. The original phantoms used in the simulation are shown in the first row of figure 2, where $\boldsymbol{c}_1$ and $\boldsymbol{c}_2$ are the stenosis and catheter phantoms, respectively. More details on the simulation method, the phantoms, and the system matrices can be found in [9].

III. Results and discussion

Fig. 1 shows the heatmap of the NRMSD of the reconstruction results using matrix compression versus the reduction factor for each channel system matrix with the original phantoms as a reference. The reduction factor represents the percentage of the system matrix coefficients used for reconstruction, with 1.0 using the full matrix. The heatmap generally shows that higher reduction factors imply a better NRMSD, i.e. better reconstruction. It is also shown that using a 0.25 reduction factor of both system matrices, a satisfactory NRMSD is obtained. The heatmap is not symmetric with the reduction factor of $\boldsymbol{S}_1$ showing more impact on the NRMSD, which implies that a lower reduction factor, namely 0.1, can be used for $\boldsymbol{S}_2$ without significantly affecting the NRMSD.

Fig. 2 displays the reconstruction results of the previously introduced data with 1000 iterations of Kaczmarz using the full system matrices in the first row, the compressed system matrices with 250 coefficients for each, and the compressed system matrices with 250 and 100 coefficients of S_1 and S_2, respectively, in the second row. Comparing the reconstructions of the different system matrices they all visually show a good quality, which agrees with the NRMSD, where the NRMSD using the full matrix is around 0.066, 25% of the full matrices is 0.070, and 17.5% of the matrices is 0.072. The use of matrix compression reduces the reconstruction time by almost a factor of 2 when using the same number of coefficients for both system matrices and by a factor of 2.6 when using a different number of coefficients for each system matrix.

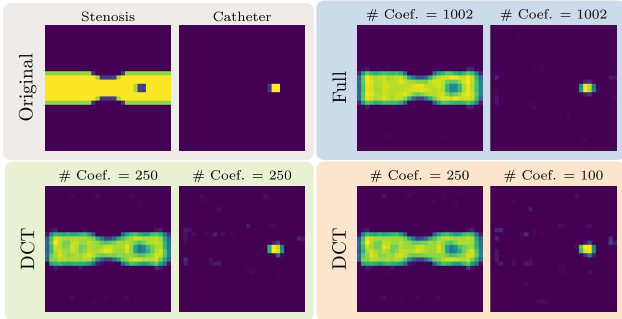

Figure 2: The figure shows reconstruction results using the full system matrices without matrix compression, the reduced system matrices with matrix compression with the same number of coefficients per channel, and with different number of coefficients per channel, respectively.

IV. Conclusion

This work confirms the feasibility of applying matrix compression for multi-contrast MPI problems for the sake of reducing the amount of data being used for reconstruction and as a result reducing the reconstruction time. It is also shown in this work that the amount of compression can be adapted for each channel in multi-contrast reconstructions without significant loss of reconstruction quality. At last, we would like to point out that though our proof of principle is restricted to 2D experimental data, the matrix compression can be applied in 3D imaging scenarios and other basis transformations as well.

Author's statement

Conflict of interest: Authors state no conflict of interest.

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