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Tailored regularization methods for multi-contrast magnetic particle imaging

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Abstract

Multi-contrast magnetic particle imaging (MPI) enables the determination of different contrasts in addition to the particle concentration. For instance it is possible to discriminate multiple tracer types that differ e.g. in the particle core size. One challenge of multi-contrast MPI is that the reconstruction problem is severely ill-posed such that in practice a perfect separation of different tracer types is not achieved. In this work, we develop a method for improving the channel separation and in turn prevent leakage from one channel into the other. Our approach exploits sparsity in both the spatial and the channel dimension. By developing a tailor regularization approach for improved multi-contrast reconstruction, we show that it is possible to significantly reduce signal leakage.

I Introduction

Multi-contrast magnetic particle imaging (MPI) [1] is a reconstruction method that allows to determine not only the concentration of the imaged magnetic nanoparticles but in addition *functional parameters* such as the their temperature [2] and the viscosity of their environment [3]. Moreover, it allows for tracer distinction based on the nanoparticles core size distribution [4]. The multi-contrast reconstruction problem is severely ill-posed because a change of the functional parameter will usually affect the induced voltage signal only marginally. For this reason it is essential to apply proper regularization techniques in order to compute a stable solution for a noisy measurement. To date, only L_2-type regularization has been applied for multi-contrast MPI, which typically leads to a blurring in space but also a blurring in direction of the functional parameter. This is also referred to a ghosting or channel leakage artifacts [5]. The purpose of the present work is to establish an L_1-type regularization approach that has the goal to significantly reduced channel leakage by promoting sparsity in both the spatial and channel dimension.

II Material and methods

The forward problem for multi-contrast MPI is given by

$$v = \sum_{i=1}^{n} S_i c_i = S c\,, \tag{1}$$

where S_i denotes the system matrix of tracer i, c_i denotes the concentration of tracer i and v is the measured signal. The state-of the art reconstruction is Tikhonov regularization with an L_2 penalty, i.e. to solve the minimization problem

$$\min_{c\geq 0} \frac{1}{2}\|Sc - v\|_2^2 + \frac{\lambda}{2}\|c\|_2^2. \tag{2}$$

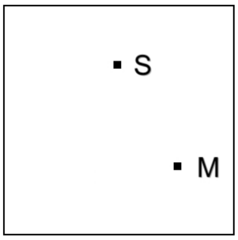

Figure 1: Phantom with dot samples of two different particle types S (core diameter 21.9 nm) and M (core diameter 25.3 nm).

II.I Regularization for multi-contrast MPI

The channel leakage is characterized by reconstructed concentrations in the wrong channel which are low compared to the correctly assigned concentration. This observation motivates sparsity promoting regularization, i.e. to minimize the Tikhonov-functional with L1 instead of the standard L2 penalty. Thus, we have to solve

$$\min_{c\geq 0} \frac{1}{2}||Sc - v||_2^2 + \lambda ||c||_1 . \tag{3}$$

Tikhonov regularization with sparsity constraints is moreover known to reduce noise in the reconstruction. The second approach aims to further reduce leakage by exploiting the fact that MPI images are typically sparse in space. Therefore, we first compute a solution by sparsity regularization. To this end, we use a threshold μ to determine the spatial support of the image and keep only those columns in the combined system matrix S that are located in the support. We then apply again the sparsity regularization on the reduced system by keeping all parameters fixed. We refer to this approach as matrix manipulation with sparsity regularization.

II.II Experimental Setup

The proposed reconstruction algorithm is evaluated using the data acquired and used in [3]. It was measured with two different particle types with a core diameter of 21.9 nm (S) and 25.3 nm (M), see Figure 1. For each of the particle types a dedicated system matrix for a 2D imaging sequence was acquired (grid size: 24 x 24 with 1 mm x 1 mm x 1 mm voxel size). Then, a phantom consisting of two dot samples (concentration 0.9g/L iron) located in the field of view was prepared and measured with the same imaging sequence as used for calibration.

III Results

The reconstruction results for the channel S (left column) and M (right column) computed by Tikhonov-regularization, Tikhonov with L_1 penalty as well as matrix manipulation with sparse regularization are shown in Figure 2. We used Kaczmarz iteration to compute the minimizer of the Tikhonov functional (2) and ADMM approach for solving the minimization problem (3). We determined for all three approaches the optimal regularization parameter by visual inspection. The reconstructions in the first row obtained by the classical Tikhonov regularization with $\lambda = 0.002$ are noisy and concentrations are assigned partly in the wrong channels. The reconstructions obtained by regularization with sparsity constraints and $\lambda = 0.008$ are sparse and noise is reduced as expected, see second row of Figure 2. Compared to the results for classical Tikhonov regularization, there is less leakage into wrong channels although there is still some wrong signal in the channel M. Finally, compared to the reconstructions computed by sparsity regularization, the reconstructions in the third row computed with the matrix manipulation approach and parameters $\lambda = 0.008$ and $\mu = 0.98$ are further improved: the leakage into wrong channels is completely suppressed. Moreover, if the values of neighbored pixels belonging to the same phantom are summed up, the reconstructed concentration values in the second and third row are close to each other.

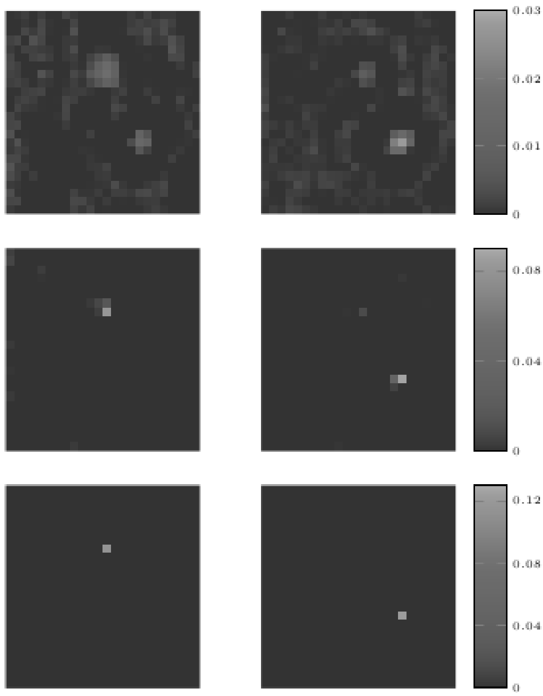

Figure 2: Multi-contrast reconstructions for the channel S (left column) and channel M (right column) computed by classical Tikhonov regularization (first row), L_1 regularization (second row) and matrix manipulation with sparse regularization (last row).

IV Discussion and Conclusions

In this work, we proposed tailored regularization methods for multi-contrast MPI, which are able to significantly reduce channel leakage artifacts. The results show that an L_1 prior in channel direction is effective to suppress the channel leakage. We note, however, that this prior should be applied if it is a-priori known that a voxel contains one of the two tracers only. A typical example for this would be a catheter labeled with a specific tracer that is distinct from a blood-pool tracer, which it displaces inside the vessel.

One general challenge with multi-spectral MPI reconstruction is that the number of unknowns grows with the number of channels while the number of equations in the imaging equation remains constant. Thus, with increasing number of channels the conditioning of the reconstruction problem gets worse. Our proposal to handle this is to reduce the number of unknowns by removing those pixels where no particles are present. This decreases the conditioning of the reconstruction problem. The results show that this improves the reconstruction quality considerably.

We used in this work an L_1 penalty to estimate the support of the particle signal. This has the downside that the L_1 prior penalized non-sparse solutions which will not give a good estimate of the support in case of larger volumes covered by particles, as for instance it will be the case in organ perfusion. In future work, it is therefore an interesting question how to derive the support without promoting sparsity, e.g. by using a Wavelet sparsifying transform.

Author's Statement

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