MULTI-CONTRAST DICTIONARY LEARNING FOR 2D COMPRESSED SENSING MRI RECONSTRUCTION

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ABSTRACT

In this work, we propose a 2-step approach for versatile dictionary learning (1st step) from MR image patches and CS MR image reconstruction (2nd step) from retrospectively 4-fold undersampled k-space data collected at 7 Tesla.

1. INTRODUCTION

Compressed Sensing (CS) has allowed a significant reduction of acquisition time in Magnetic Resonance Image (MRI) by massively under-sampling the k-space. CS-MRI reconstruction relies on a sparsifying dictionary Ψ to model the sought-for image with a few non-zero coefficients in an appropriate domain (e.g., wavelets) and promote sparsity in this domain. Instead of considering a fixed Ψ, Dictionary Learning (DL) has allowed for the fitting of more suited sparsifying MR image representations. In the MRI literature, blind CS has been proposed as the optimal solution to both DL and CS image reconstruction [1]. However, this approach is computationally demanding and requires learning a new dictionary for each dataset. Here, we propose a 2-step approach instead: first, a complex-valued dictionary Ψ is learnt from several contrast-weighted MR images and second, we use this versalite Ψ during CS reconstruction.

2. MATERIALS AND METHODS

The dictionary Ψ was learnt from overlapping image patches of fully-sampled MR images. The latter were collected using a quantitative simultaneous multi-parametric MRI protocol (QuiCS) on a 7 Tesla Magnetom scanner [2]. Four healthy volunteers were recruited for MRI scanning. Twelve 3D contrast images (2.3 mm iso.) were collected in each participant to enable quantification of M_0, R_1, R_2 and diffusion parameters. In total, we used from 80 % of the database (training set) for DL and the remaining 20 % were let for testing on retrospective CS reconstruction.

1st: DL step. We used the online DL and sparse-coding algorithm [3] available in the Scikit-learn package [1]. Two real-valued Ψ were learnt separately for the real and imaginary parts from MR image patches. Hundreds of 2D overlapping patches were used to cover the whole image. On a preliminary study, we cross-validated the number of components (number of columns in Ψ), the regularization parameter involved in DL and the patch size (number of rows in Ψ) and eventually set them to 100, 1 and 10×10, respectively. For the multi-contrast DL, we pulled the 12 contrast images together.

2nd: Reconstruction step. As regards reconstruction from retrospectively undersampled k-space data, we injected the learnt Ψ and rely on a analysis-based prior to promote sparsity in the image domain using the ℓ_1 norm over image patches. Hence, we implemented a primal-dual algorithm [4] in the PISAP package (`https://github.com/neurospin/pisap`).

[1] `http://scikit-learn.org/`

3. RESULTS

We compared the CS MRI reconstruction results in terms of structural similarity (SSIM) metric and analysed different competing scenarios (eg, contrast-specific vs multi-contrast DL). We observed that our multi-contrast Ψ achieved similar SSIM performances as the contrast-specific ones, which allows us to save a significant computational burden (i.e. 12-fold acceleration).

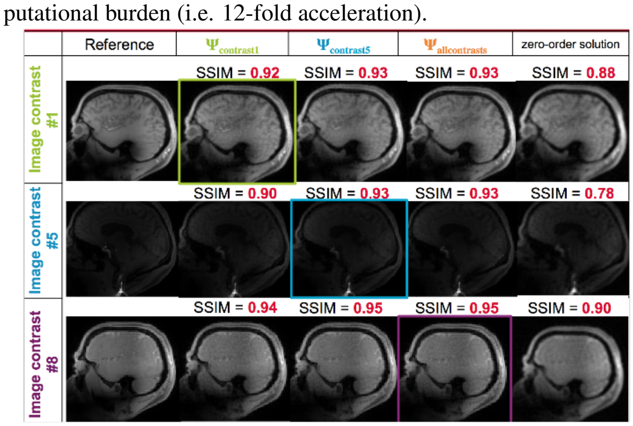

Fig. 1. Impact of single vs multi-contrast Ψ on image quality at the CS reconstruction stage.

4. CONCLUSION AND PERSPECTIVES

This suggests that a 2-step DL approach in which the dictionary is not specifically learnt from a specific contrast is a viable alternative to blind CS. Also, we will show complementary results that supports the versatility of DL learnt from different image resolutions.

5. REFERENCES

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