Efficient Exploitation of Image Repetitions in MR Reconstruction

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Editors: Under Review for MIDL 2022

Abstract

Parallel imaging with multiple receiver coils has become a standard in many MRI applications. Methods based on *Deep Learning* (DL) were shown to allow higher acceleration factors than conventional methods. In the case of *diffusion-weighted imaging* (DWI) where multiple repetitions of a slice are acquired, a DL-based reconstruction method should ideally make use of available redundancies. Based on the concept of *Deep Sets* which outlines a generic approach for operating on set-structured data, this work investigates the benefits of joint reconstruction of image repetitions in DWI. Evaluations show that, compared to separate processing of repetitions, reconstructions can be improved both qualitatively and quantitatively by incorporating simple and computationally inexpensive operations into an existing DL architecture.

Keywords: MRI, DWI, Deep Learning, Deep Sets, Image Reconstruction, Liver Diffusion

1. Introduction

DWI has shown high clinical value as a cancer biomarker, for example, in abdominal imaging (Taouli and Koh, 2010). However, as acquisitions are predominantly based on single-shot echo-planar imaging (EPI), image quality can suffer from strong signal decay, limited resolution as well as susceptibility-induced distortions. Parallel imaging is a common technique for shortening the EPI train. In the context of abdominal DWI, however, conventional reconstruction techniques (Pruessmann et al., 1999) preclude the usage of acceleration factors $R > 2$ as these typically lead to excessive noise amplification. More recently, DL-based methods demonstrated success in further pushing acceleration factors in MR reconstruction (Muckley et al., 2021). Given the repetitive nature of DWI which acquires the same slice multiple times for averaging, a DL-based solution which exploits redundancies within image repetitions is potentially beneficial. Deep Sets (Zaheer et al., 2017) provide a framework for dealing with non-sequential, set-structured data and ensuring desirable properties, such as in-variance with respect to permutations and set size. Based on it, this work aims to demonstrate the value of DL-based joint reconstruction of image sets in the case of abdominal DWI.
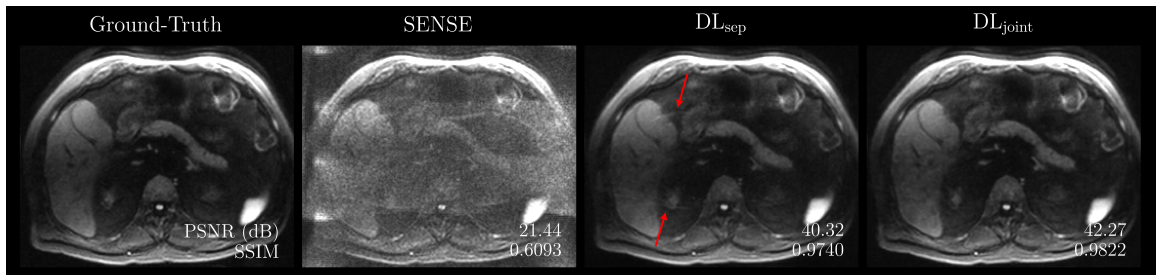
Figure 1: DWI reconstructions produced by SENSE, DL_{sep} and DL_{joint} for $R = 4$. Red arrows in the DL_{sep} reconstruction indicate residual aliasing artifacts.

2. Methods

This work employed an unrolled DL architecture for reconstruction which was proposed previously in the context of partial Fourier imaging (Gadjimuradov et al., 2022). Across five iterations, it alternates between a series of ten recurrent convolutional layers for regularization and data consistency operations. Following the idea of Deep Sets, the N available repetitions of a slice are stacked along the batch dimension of the input. After passing through five layers of the regularization network, the corresponding set/batch of feature maps $\{\boldsymbol{F}_n\}_{n=1}^N$ is aggregated to its mean along the batch dimension $\boldsymbol{F}_{\mathrm{aggr}} \in \mathbb{R}^{C \times H \times W}$ where C is the number of feature channels and H and W represent the spatial dimensions. Information sharing among set elements is hence realized by concatenation with the set aggregate along the channel dimension:

$$\boldsymbol{F}'_n = \mathrm{concat}(\boldsymbol{F}_n, \boldsymbol{F}_{\mathrm{aggr}}) \in \mathbb{R}^{2C \times H \times W} . \tag{1}$$

3. Data and Evaluation

Using a prototypical single-shot EPI and a b-value of $800\,\mathrm{s/mm^2}$ with 20 repetitions for abdominal DWI, 37 healthy subjects were scanned on 1.5 and 3 T MR scanners (MAGNE-TOM, Siemens Healthcare, Erlangen, Germany) and randomly assigned into training (31), validation (3) and test (3) pools. The acquired raw data was compressed to 8 channels in the preprocessing and retrospectively subsampled ($R = 4$) for both training and evaluation. Conventional SENSE reconstructions (Pruessmann et al., 1999) were provided as network inputs. The employed network was trained and evaluated in two configurations, DL_{sep} and DL_{joint}, representing separate and joint reconstruction of repetitions, respectively.

4. Results

Figure 1 shows the qualitative comparison of reconstructions obtained after magnitude averaging of the 20 repetitions. At $R = 4$, SENSE produces clinically non-acceptable noise enhancement. Further, the conventional reconstruction suffers from residual aliasing due to inaccuracies in sensitivity estimation. DL_{sep} performs well in terms of denoising but fails to

remove residual aliasing sufficiently. In contrast, DL_{joint} manages to compensate effectively for both noise and aliasing. The quantitative evaluation on the entire test set further underlines the benefits of joint reconstruction as DL_{sep} can be outperformed significantly ($p < 0.05$) in terms of PSNR ($40.35\,dB$ vs. $38.31\,dB$) and SSIM (0.9775 vs. 0.9674).

5. Discussion and Conclusion

Joint reconstruction of image repetitions introduces another dimension of regularization as it facilitates the distinction of noise from important image structures. Structured artifacts, such as aliasing shown in Figure 1, can be mitigated as well given that some repetitions may be less affected than others. The implementation of Deep Sets in this work enabled information exchange by providing set elements with first-order set statistics. Our results show that performing the respective aggregation and concatenation of feature maps once within the network was already sufficient to observe improved reconstruction quality. As these operations can be easily integrated into arbitrary DL architectures and come with negligible computational overhead, the presented approach is highly efficient. Compared to DL_{sep}, the number of trainable parameters rose by $5.8\,\%$ for DL_{joint} to accommodate for the doubled feature channels after concatenation. However, this is orders of magnitude below the parameter increase that would be necessary for implementing joint reconstruction via 3D convolutions, for example. Moreover, arranging repetitions in a 3D volume violates the requirement of permutation-equivariance as the ordering of the repetitions would influence the result. In conclusion, the proposed implementation of Deep Sets enables joint reconstruction in an efficient manner under consideration of important in-variance properties and is therefore useful in applications where multiple image realizations without sequential context are available.

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