Diffusion-Weighted Imaging with Learned Nonlinear Latent Space Modeling and Self-Supervised Reconstruction (DeepDWI)

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***Abstract*— Keep the abstract to 250 words or less.**

***Index Terms*— Diffusion-weighted imaging, Image reconstruction, Neural network, Latent space, Self-supervised learning**

I. Introduction

HIGH-dimensional magnetic resonance imaging (HD-MRI), referring to the acquisition, reconstruction, and analysis of multi-dimensional imaging, in contrast to single-contrast-weighted, static, and two-dimensional imaging. Examples of HD-MRI include but are not limited to magnetic resonance spectroscopic imaging (MRSI) [?], diffusion-weighted imaging (DWI) [?], and magnetic resonance fingerprinting (MRF) [?]. MRSI uses multiple readout gradients to acquire multiple echo images for the computation of spatially resolved metabolic distribution. DWI utilizes spatially and angularly varying diffusion encoding gradients to obtain multi-contrast diffusion-weighted images as a probe into tissue microstructure. MRF designs a T_1- and T_2-prepared pseudo-randomized sequence to acquire time-resolved transient-state images, which are matched with Bloch-equation generated dictionaries [?] for simultaneous quantitative T_1 and T_2 mapping.

HD-MRI, however, conventionally requires long scan time and high computational burden. Advances in parallel imaging [?], [?], [?], [?], [?] and compressed sensing [?], [?], [?] have enabled accelerated acquisition for HD-MRI. For instance, Lam et al. [?] proposed SPectroscopic Imaging by exploiting spatiospectral CorrElation (SPICE) based on the low-rank modeling. McGivney et al. [?] proposed the use of the singular value decomposition (SVD) and thresholding to compress the MRF dictionary and to reduce the computational burden. Further, Christodoulou et al. [?] proposed MR Multitasking with higher-order SVD (HOSVD) modeling and iterative reconstruction for motion-resolved quantitative T_1 and T_2 mapping. However, the use of patch-based SVD still requires long computational time.

Beyond sparsity constraint and low-rank modeling, advanced neural networks, e.g. denoising autoencoder [?], have been explored for HD-MRI reconstruction. Lam et al. [?] proposed to first learn a DAE model from physics-informed simulated data and then incorporate the learned DAE model as a regularizer in iterative reconstruction. This concept was adopted by Mani et al. [?] for joint k-q-space DWI reconstruction using learned DAE *priors*. Further, Arefeen et al. [?] proposed to replace the conventional SVD-based linear subspace modeling [?] by the latent decoder model within DAE for improved multi-T_2-weighted image reconstruction. Besides learning a *prior* based on simulated data for regularization or latent space modeling, Hammernik et al. [?] and Aggarwal et al. [?] proposed supervised learning unroll reconstruction networks, which are trained by fully-sampled in vivo data. Yaman et al. [?], [?] proposed the self-supervised learning unroll network without fully-sampled data, which builds upon the concept of cross-validation in machine learning.

The capability of DAE to learn diffusion MRI models, however,

II. Theory

III. Methods

A. Learning a VAE

IV. Results

V. Discussion

VI. Conclusion

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