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

Zhengguo Tan, Julius Glaser, Patrick A Liebig, Annika Hofmann, Frederik B Laun, Florian Knoll

***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) has been an emerging and flourishing field, which has achieved substantial improvements in terms of spatiotemporal fidelity. Instead of the conventional two-dimensional static single-contrast-weighted imaging, HD-MRI acquires and reconstructs multi-dimensional information. For instance, Brown et al. [1] proposed magnetic resonance spectroscopic imaging (MRSI), which uses multiple readout gradients to acquire multiple echo images for the computation of spatially resolved metabolic distribution. Le BiHan et al. [2] proposed diffusion-weighted imaging (DWI), which utilizes spatially and angularly varying diffusion encoding gradients in combination with fast echo-planar imaging (EPI) readouts [3] to obtain multi-contrast diffusion-weighted images as a probe into tissue microstructure. Ma et al. [4] proposed magnetic resonance fingerprinting (MRF) which consists of a T_1- and T_2-prepared pseudo-randomized sequence to acquire time-resolved transient-state images and a Bloch-equation-based dictionary matching algorithm [5] for simultaneous quantitative T_1 and T_2 mapping.

HD-MRI, however, conventionally requires long scan time. Advances in parallel imaging [6]–[10] and compressed sensing [11]–[13] have enabled accelerated acquisition for HD-MRI. In particular, the low-rank modeling and regularization [14] has been a powerful tool in reducing the dimensionality of high-dimensional data, which enables accelerated acquisition and high spatiotemporal-resolution reconstruction. Usually, singular value decomposition (SVD) is used to learn a truncated temporal basis function from a large-scale physics-informed dictionary [15]–[17]. The temporal basis function is then integrated with the MRI forward model, i.e. the sensitivity encoding operator [9], for joint reconstruction of the corresponding spatial basis images. In addition, low-rank regularization can be added to the joint reconstruction [18].

Beyond the low-rank technique, advanced neural networks, e.g. autoencoder [19], have been explored for HD-MRI reconstruction and proven to supply more accurate representations of high-dimensional data than SVD. Lam et al. [20], [21] proposed to first learn a denoising autoencoder (DAE) model from a physics-informed simulated dictionary and then incorporate the learned DAE model as a regularizer in iterative reconstruction. Further, Arefeen et al. [22] proposed to replace the conventional SVD-based linear subspace modeling [15] by the latent decoder model within DAE for improved T_2-weighted image reconstruction. The capability of DAE to learn diffusion MRI models, however, is open to questions. DAE is composed of sequential fully connected layers with nonlinear activation functions. This simple architecture may fail to learn complicated functions. DWI signal is such an example. The standard diffusion tensor model [23] consists of six tensor elements, and forms DWI signals based on the multiplication of exponential functions. Moreover, DWI signals can be described with more complicated models, e.g. the ball-and-stick model [24], which involves even more parameters.

Besides learning a *prior* based on simulated data for regularization or latent space modeling, Hammernik et al. [25] and Aggarwal et al. [26] proposed supervised learning unroll reconstruction networks, which are trained by fully sampled in vivo data. Yaman et al. [27], [28] proposed the self-supervised learning unroll network without fully-sampled data, which builds upon the concept of cross-validation in machine learning. However, in the case of DWI, it is rather challenging to acquire fully-sampled data for the training of a regularization

This work was supported in part by German Research Foundation (DFG) under projects 513220538 and 512819079, project 500888779 in the Research Unit RU5534 for MR biosignatures at UHF, and by the National Institutes of Health (NIH) under grants R01 EB024532 and P41 EB017183. In addition, scientific support and HPC resources were provided by the Erlangen National High Performance Computing Center (NHR) of Friedrich-Alexander-University Erlangen-Nuremberg (FAU) under the NHR project b143dc. NHR is funded by federal and Bavarian state authorities. NHR@FAU hardware is partially funded by DFG under project 440719683.

Z. T. was with the Department Artificial Intelligence in Biomedical Engineering (AIBE), FAU, Erlangen, Germany. He is now with the Michigan Institute for Imaging Technology and Translation (MIITT), Department of Radiology, University of Michigan, Ann Arbor, MI 48109 USA (e-mail: zgtan@med.umich.edu).

J. G. is with the Department Medical Engineering, FAU, Erlangen, Germany (e-mail: julius.glaser@fau.de).

P. A. L. is with Siemens Healthcare GmbH, Erlangen, Germany (e-mail: patrick.liebig@siemens-healthineers.com).

A. H. is with the Department AIBE, FAU, Erlangen, Germany (e-mail: annika.ah.hofmann@fau.de).

F. B. L. is with the Institute of Radiology, University Hospital Erlangen, FAU, Erlangen, Germany (e-mail: Frederik.Laun@uk-erlangen.de).

F. K. is with the Department AIBE, FAU, Erlangen, Germany (e-mail: florian.knoll@fau.de).

functional. First, fully-sampled DWI requires a longer echo train in EPI, which not only elongates the scan time but also increases off-resonance-induced geometric distortion. Second, there exists a wide range of diffusion modes, thereby requiring a larger dataset than the two-dimensional imaging scenario.

In this work, we aim to develop a generalized DWI reconstruction framework with learned nonlinear latent space modeling and self-supervised reconstruction, dubbed DeepDWI.

II. Theory

III. Methods

A. Learning a VAE

IV. Results

V. Discussion

VI. Conclusion

Acknowledgment

Z. T. thanks to Ms. Soundarya Soundarresan for her work and discussion on denoising autoencoder. Z. T. thanks to Dr. Xiaoqing Wang for the discussion on self-supervised learning.

References

[1] T. R. Brown, B. M. Kincaid, and K. Ugurbil, "NMR chemical shift imaging in three dimensions," *Proc. Natl. Acad. Sci. USA*, vol. 79, pp. 3532–3526, 1982.

[2] D. Le Bihan, E. Breton, D. Lallemand, P. Grenier, E. Cabanis, and M. Laval-Jeantet, "MR imaging of intravoxel incoherent motions: application to diffusion and perfusion in neurologic disorders," *Radiology*, vol. 161, pp. 401–407, 1986.

[3] P. Mansfield, "Multi-planar image formation using NMR spin echoes," *J Phys C*, vol. 10, pp. 55–58, 1977.

[4] D. Ma, V. Gulani, N. Seiberlich, K. Liu, J. L. Sunshine, J. L. Duerk, and M. A. Griswold, "Magnetic resonance fingerprinting," *Nature*, vol. 495, pp. 187–192, 2013.

[5] M. Doneva, P. Börnert, H. Eggers, C. Stehning, J. Sénégas, and A. Mertins, "Compressed sensing for magnetic resonance parameter mapping," *Magn. Reson. Med.*, vol. 64, pp. 1114–1120, 2010.

[6] P. B. Roemer, W. A. Edelstein, C. E. Hayes, S. P. Souza, and O. M. Mueller, "The NMR phased array," *Magn. Reson. Med.*, vol. 16, pp. 192–225, 1990.

[7] D. K. Sodickson and W. J. Manning, "Simultaneous acquisition of spatial harmonics (SMASH): Fast imaging with radiofrequency coil arrays," *Magn. Reson. Med.*, vol. 38, pp. 591–603, 1997.

[8] K. P. Pruessmann, M. Weiger, M. B. Scheidegger, and P. Boesiger, "SENSE: Sensitivity encoding for fast MRI," *Magn. Reson. Med.*, vol. 42, pp. 952–962, 1999.

[9] K. P. Pruessmann, M. Weiger, P. Börnert, and P. Boesiger, "Adcances in sensitivity encoding with arbitrary k-space trajectories," *Magn. Reson. Med.*, vol. 46, pp. 638–651, 2001.

[10] M. A. Griswold, P. M. Jakob, R. M. Heidemann, M. Nittka, V. Jellus, J. Wang, B. Kiefer, and A. Haase, "Generalized autocalibrating partially parallel acquisitions (GRAPPA)," *Magn. Reson. Med.*, vol. 47, pp. 1202–1210, 2002.

[11] M. Lustig, D. Donoho, and J. M. Pauly, "Sparse MRI: The application of compressed sensing for rapid MR imaging," *Magn. Reson. Med.*, vol. 58, pp. 1182–1195, 2007.

[12] K. T. Block, M. Uecker, and J. Frahm, "Undersampled radial MRI with multiple coils. Iterative image reconstruction using a total variation constraint," *Magn. Reson. Med.*, vol. 57, pp. 1186–1098, 2007.

[13] Z.-P. Liang, "Spatiotemporal imaging with partially separable functions," in *4th IEEE International Symposium on Biomedical Imaging: From Nano to Macro (ISBI'4)*, 2007, pp. 988–991.

[14] J.-F. Cai, E. J. Candès, and Z. Shen, "A singular value thresholding algorithm for matrix completion," *SIAM. J. Optim.*, vol. 20, pp. 1956–1982, 2010.

[15] C. Huang, C. G. Graff, E. W. Clarkson, A. Bilgin, and M. I. Altbach, "T_2 mapping from highly undersampled data by reconstruction of principal component coefficient maps using compressed sensing," *Magn. Reson. Med.*, vol. 67, pp. 1355–1366, 2012.

[16] F. Lam and Z.-P. Liang, "A subspace approach to high-resolution spectroscopic imaging," *Magn. Reson. Med.*, vol. 71, pp. 1349–1357, 2014.

[17] D. F. McGivney, E. Pierre, D. Ma, Y. Jiang, H. Saybasili, V. Gulani, and M. A. Griswold, "SVD compression for magnetic resonance fingerprinting in the time domain," *IEEE Trans. Med. Imaging*, vol. 33, pp. 2311–2322, 2014.

[18] J. I. Tamir, M. Uecker, W. Chen, P. Lai, M. T. Alley, S. S. Vasanawala, and M. Lustig, "T_2 shuffling: Sharp, multicontrast, volumetric fast spin-echo imaging," *Magn. Reson. Med.*, vol. 77, pp. 180–195, 2017.

[19] G. E. Hinton and R. R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science*, vol. 313, pp. 504–507, 2006.

[20] F. Lam, Y. Li, and X. Peng, "Constrained magnetic resonance spectroscopic imaging by learning nonlinear low-dimensional models," *IEEE Trans. Med. Imaging*, vol. 39, pp. 545–555, 2019.

[21] M. Mani, V. A. Magnotta, and M. Jacob, "qModeL: A plug-and-play model-based reconstruction for highly accelerated multi-shot diffusion MRI using learned priors," *Magn. Reson. Med.*, vol. 86, pp. 835–851, 2021.

[22] Y. Arefeen, J. Xu, M. Zhang, Z. Dong, F. Wang, J. White, B. Bilgic, and E. Adalsteinsson, "Latent signal models: Learning compact representations of signal evolution for improved time-resolved, multi-contrast MRI," *Magn. Reson. Med.*, vol. 90, pp. 483–501, 2023.

[23] P. J. Basser, J. Mattiello, and D. Le Bihan, "MR diffusion tensor spectroscopy and imaging," *Biophys. J.*, vol. 66, pp. 259–267, 1994.

[24] T. E. J. Behrens, M. W. Woolrich, M. Jenkinson, H. Johansen-Berg, R. G. Nunes, S. Clare, P. M. Matthews, J. M. Brady, and S. M. Smith, "Characterization and propagation of uncertainty in diffusion-weighted MR imaging," *Magn. Reson. Med.*, vol. 50, pp. 1077–1088, 2003.

[25] K. Hammernik, T. Klatzer, E. Kobler, M. P. Recht, D. K. Sodickson, T. Pock, and F. Knoll, "Learning a variational network for reconstruction of accelerated MRI data," *Magn. Reson. Med.*, vol. 79, pp. 3055–3071, 2018.

[26] H. K. Aggarwal, M. P. Mani, and M. Jacob, "MoDL: Model-based deep learning architecture for inverse problems," *IEEE Trans. Med. Imaging*, vol. 38, pp. 394–405, 2018.

[27] B. Yaman, S. A. H. Hosseini, S. Moeller, J. Ellermann, K. Uğurbil, and M. Akçakaya, "Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data," *Magn. Reson. Med.*, vol. 84, pp. 3172–3191, 2020.

[28] B. Yaman, S. A. H. Hosseini, and M. Akçakaya, "Zero-shot self-supervised learning for MRI reconstruction," in *10th International Conference on Learning Representations (ICLR'10)*, 2022.