**Application of Deep Learning to Quantify Brain Microstructure**

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1. Introduction

Diffusion-weighted magnetic resonance imaging (DW MRI) offers valuable insights into cellular structures, making it a powerful tool for the non-invasive evaluation of brain microstructure. This modality is particularly sensitive to natural processes of brain maturation and aging, and various neurological disorders [1]. However, accurate modeling of the DW signal is crucial for extracting quantitative indicators, especially when the acquisition procedure is limited.

1. Description of the problem

Diffusion tensor imaging (DTI) [2] is a widely used technique for modeling the DW signal, but interpreting its data can be challenging as it only captures the primary direction of diffusion [1]. An alternative approach involves using multicompartment biophysical models that assume specific tissue geometries and can directly estimate key microstructural parameters, making data interpretation easier [3]. Two of the most popular biophysical models are Neurite Orientation Dispersion and Density Imaging (NODDI) [4] and the Spherical Mean Technique (SMT) [5] (see Fig.1). Microstructural parameters derived from multicompartment models are typically calculated using numerical optimization procedures. However, these methods require more complex and time-consuming acquisition protocols, including a specific number of DW volumes, than those commonly used in clinical practice. This complexity significantly limits the practical application of biophysical models in clinical settings.

Obraz zawierający tekst, diagram, Czcionka, linia

Opis wygenerowany automatycznie

**Fig.1.** Distribution of the total DW signal between different compartments of the A. NODDI and B. SMT models.

1. Related work

Research in the literature has explored the potential application of deep learning to estimate parameters of multicompartment models, especially the NODDI [6,7]. However, these studies are quite limited in scope. They often focus only on the effects of a reduced number of DW volumes, while employing acquisition schemes that are not commonly used in clinical practice.

1. Solution to the problem

The study utilized the HCP WU-Minn data [8], which originally included 90 gradient directions for three b-values (1000, 2000, and 3000 s/mm2). To simulate acquisition protocols more representative of clinical settings [9], the data were downsampled and interpolated using spherical harmonics to generate three separate datasets with b = 1000 s/mm² and 32, 15, and 6 gradient directions. Microstructural parameters were estimated using both traditional numerical optimization techniques and a deep learning-based U-net model. Parameters derived from the original, full-resolution acquisition were used as the ground truth for comparison. Performance evaluation was conducted using the Mean Structural Similarity Index Measure (MSSIM).   
A summary of the results is provided in Table 1.

**Table 1.** MSSIM results of the U-Net and a standard numerical method across different acquisition schemes, assessed for various parameters of the SMT and NODDI models.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **32 volumes, b1000** | | **15 volumes, b1000** | | **6 volumes, b1000** | |
| **Microstructural parameter** | **DL model** | **Numerical method** | **DL model** | **Numerical method** | **DL model** | **Numerical method** |
| **vic** | 0.950 | 0.703 | 0.947 | 0.704 | 0.945 | 0.698 |
| **vec** | 0.785 | 0.099 | 0.791 | 0.103 | 0.784 | 0.116 |
| **viso** | 0.884 | 0.484 | 0.887 | 0.488 | 0.867 | 0.495 |
| **vin** | 0.833 | 0.225 | 0.823 | 0.218 | 0.823 | 0.065 |

1. Conclusions and future work

Deep learning models significantly outperform traditional numerical method, achieving MSSIM values over 0.8 for all parameters except vec, even with only 6 gradient directions.

To better assess ability of artificial intelligence to estimate microstructural parameters, we should move beyond U-Net to more advanced models like GANs, and focus on metrics more clinically relevant than MSSIM, particularly in key regions of the brain. It's also crucial to determine if these models can effectively differentiate parameter values between healthy individuals and those with diseases to support accurate diagnosis.

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References

1. L. J. O’Donnell, et al.: *An introduction to diffusion tensor image analysis*, Neurosurgery clinics 22(2), 185-196, 2011.
2. P. J. Basser, et al.: *MR diffusion tensor spectroscopy and imaging*, Biophysical journal 66(1), 259-267, 1994.
3. I. O. Jelescu, et al*.: Design and validation of diffusion MRI models of white matter*, Frontiers in physics 5, 61, 2017.
4. H. Zhang, et al.: *NODDI: practical in vivo neurite orientation dispersion and density imaging of the human brain*, Neuroimage 61(4), 1000-1016, 2012.
5. E. Kaden, et al.: *Quantitative mapping of the per‐axon diffusion coefficients in brain white matter*, Magnetic resonance in medicine 75(4), 1752-1763, 2016.
6. E. K. Gibbons, et al.: *Simultaneous NODDI and GFA parameter map generation from subsampled q‐space imaging using deep learning*, Magnetic resonance in medicine 81(4), 2399-2411, 2019.
7. A. Faiyaz, et al.: *Single‐shell NODDI using dictionary‐learner‐estimated isotropic volume fraction*, NMR in biomedicine 35(2), 2022
8. D. C. Van Essen, et al.: *The WU-Minn human connectome project: an overview*, Neuroimage 80, 62-79, 2013.
9. M. D. C. Valdés Hernández, et al.: *Rationale, design and methodology of the image analysis protocol for studies of patients with cerebral small vessel disease and mild stroke*. Brain and behavior 5(12), 2015.