Validation of NODDI estimation of dispersion anisotropy in V1 of the human neocortex

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Authors:

Maira Tariq¹, Michiel Kleinnijenhuis², Anne-Marie van Cappellen van Walsum³, Gary Zhang¹

Institutions:

¹University College London, London, United Kingdom, ²University of Oxford, Oxford, United Kingdom, ³Radboud University Medical Centre, Nijmegen, Netherlands

Introduction:

This work validates the estimation of neurite dispersion anisotropy in the brain, using Bingham-NODDI [1], an extension of the diffusion MRI technique called NODDI [2]. The original NODDI provides indices of neurite (axons and dendrites) morphology that are sensitive and specific to microstructural changes [3-7]. Bingham-NODDI additionally allows the estimation of neurite dispersion anisotropy, which can enhance the accuracy of tractography algorithms [8]. The in vivo feasibility of Bingham-NODDI has been evaluated in [1]. The present study validates its indices using high-resolution ex vivo imaging data of the human primary visual cortex (V1), a well characterised region of the neocortex known to include fibres that fan or bend into the cortical layers.

Methods:

DATA: Diffusion weighted images were acquired for a fixed sample of the human V1 (as used in [9]), using a 9.4T small animal scanner. The acquisition included b=[0,1000,4000,8000,12000,16000,20000]s/mm² with δ =8.4ms, Δ =12.8ms, TE=27ms, and 60 gradient directions. The images were of 0.2mm isotropic resolution with FOV=28.8x28.8mm, covering the cortex and the underlying white matter (WM).

MODEL: NODDI is a multi-compartment model that accounts for the dispersion of neurites with an orientation density function (ODF). The original Watson-NODDI uses the Watson distribution [10] which can only model isotropic dispersion about the dominant orientation (μ_1); the Bingham-NODDI instead uses the Bingham distribution [10] and enables the modelling of anisotropic dispersion. Both models estimate the neurite density (v_{in}), μ_1 and the orientation coherence (κ) about μ_1 . Bingham-NODDI additionally estimates the primary dispersion orientation (μ_2) and the associated coherence parameter (β). The eigenvalues of the scatter matrix of an ODF, τ_1 and τ_2 , represent the relative neurite concentrations along μ_1 and μ_2 , and are functions of κ and β , as described in [1]. The dispersion anisotropy is quantified as: DAI=(τ_2 - τ_3)/ τ_1 .

FITTING: Both models were fitted to the data using the NODDI Matlab Toolbox. Watson-NODDI parameters were obtained using the optimisation procedure described in [2]; the intrinsic diffusivity was also fitted. The maximum-likelihood parameters from the Watson-NODDI fit were used to initialise the fitting for Bingham-NODDI. The parameters from the two models were evaluated using the Bayesian Information Criterion (BIC), a standard model comparison metric.

Results:

PARAMETER EVALUATION: Fig.1 shows the maps of the Bingham-NODDI estimates, β and DAI. The DAI map shows highest values in WM that gradually get lower as the WM fibres disperse into the cortical grey matter (GM), signifying the presence of fanning and bending fibres in the cortical areas. The β plot has a contrast very similar to DAI, but the higher values are limited to WM regions, unlike the higher DAI values, showing that the WM fibres can be traced extending into the cortex using the DAI estimates.

MODEL COMPARISON: The BIC maps in Fig.2 demonstrate that Bingham-NODDI explains the data better than Watson-NODDI. Watson-NODDI fits the data particularly poorly in WM regions, especially near the WM/GM boundary, areas where dispersion anisotropy is expected. Fig.2 also shows that the κ maps from Bingham-NODDI have higher intensity in WM, as well as the various cortical layers, compared to Watson-NODDI. This increased intensity and contrast is more closely aligned with histology, as it is found in [9] that Watson-NODDI underestimates the actual neurite coherence.



Fig.1 Maps of the novel parameters of Bingham-NODDI, (a) β and (b) DAI, for a slice of the primary visual cortex sample.



Fig.2 Maps of \mathcal{K} estimates and quality of fit (BIC) for the two NODDI models, for a slice of the primary visual cortex sample.

Conclusions:

We show that Bingham-NODDI is able to capture the cortical fibres known to exhibit fanning/bending, with a measure of dispersion anisotropy. This has implications for enhancing our understanding of the brain microstructure and connectivity, even in regions of complex cytoarchitecture, like the cortex.

Imaging Methods:

Diffusion MRI²

Modeling and Analysis Methods:

Diffusion MRI Modeling and Analysis ¹

Keywords: MRI

NORMAL HUMAN

Other - NODDI, Diffusion MRI, Dispersion anisotropy, Bingham Distribution, Ex vivo

$^{1\left| 2\right| }$ Indicates the priority used for review

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Please indicate which methods were used in your research:

Diffusion MRI

For human MRI, what field strength scanner do you use?

If Other, please list - 9.4T

Which processing packages did you use for your study?

Other, Please list - NODDI toolbox, ITK-SNAP

FSL

Provide references in author date format

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