



**HAL**  
open science

# Investigating Diffusion-MRI based neurite density estimation model dependency: an in-vivo study on the HCP dataset

Mauro Zucchelli, Maxime Descoteaux, Gloria Menegaz

## ► To cite this version:

Mauro Zucchelli, Maxime Descoteaux, Gloria Menegaz. Investigating Diffusion-MRI based neurite density estimation model dependency: an in-vivo study on the HCP dataset. ISMRM 2018 - International Society for Magnetic Resonance in Medicine, Jun 2018, Paris, France. hal-01831823

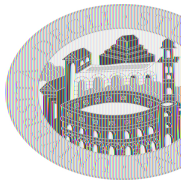
**HAL Id: hal-01831823**

**<https://inria.hal.science/hal-01831823v1>**

Submitted on 12 Dec 2018

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



# Investigating Diffusion-MRI based neurite density estimation model dependency: an in-vivo study on the HCP dataset



Mauro Zucchelli<sup>1,3</sup>, Maxime Descoteaux<sup>2</sup>, and Gloria Menegaz<sup>1</sup>

<sup>1</sup>University of Verona (Italy), <sup>2</sup>University of Sherbrooke (Canada), <sup>3</sup>INRIA, Sophia Antipolis-Méditerranée (France)

---

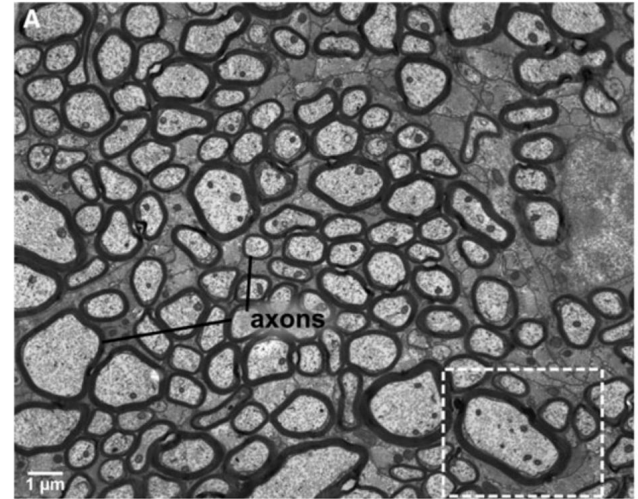
**ISMRM 2018 Paris**  
**Time: 09:15, 18<sup>th</sup> June**  
**Number: 3235**  
**Computer N°: 41**

**SCIL**  
Sherbrooke Connectivity Imaging Lab

# Neurite Density and Diffusion MRI

---

- **Neurite density**<sup>1,2,3,4,5</sup> is one of the most promising microstructural features that can be estimated from **Diffusion-MRI** multi-shell data
- Recent years have seen a proliferation of **Multi-Compartment models** developed to estimate the neurite density



*Nilsson et. al. "The role of tissue microstructure and water exchange in biophysical modelling of diffusion in white matter" Magn Reson Mater Phy (2013) 26:345370*

# Multi-Compartment models

---

- Multi-Compartment models represents the diffusion signal as a weighted sum of *compartments*

INTRA

EXTRA

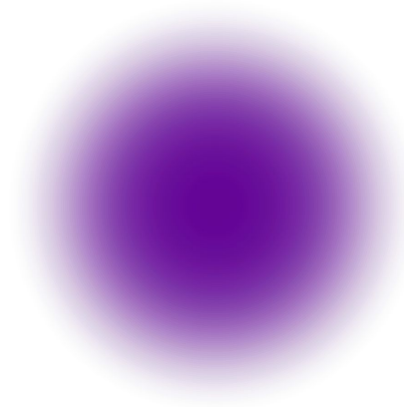
CSF



+



+



# Neurite Density and Diffusion MRI

---

- Neurite density can be calculated from Multi-Compartment models as the **intra-axonal volume fraction** ( $\nu_{ia}$ )

$$F(b, \vec{\mathbf{u}}, \vec{\mathbf{v}}) = \nu_{ia} F_{ia}(b, \vec{\mathbf{u}}, \vec{\mathbf{v}}) + \nu_{ea} F_{ea}(b, \vec{\mathbf{u}}, \vec{\mathbf{v}}) + \nu_{csf} F_{csf}(b)$$

- Recent years have seen a **proliferation**<sup>1,2,3,4,5,6,7,9,10</sup> of Multi-Compartment models
  - Each of these models makes different **assumptions** about the values of the diffusivity coefficient and the number of compartments
-

# Spherical Mean Technique

---

- This MC representation of the diffusion signal is valid only for fibers **aligned** in a single direction
- We can **convolve** the single fiber signal to the *fiber Orientation Distribution Function (fODF)*

$$E(b, \vec{u}) = \int_{\vec{v} \in S^2} \rho(\vec{v}) F(b, \vec{u}, \vec{v}) d\vec{v}$$

$$\rho(\vec{v}) = \sum_{l=0, \text{even}}^{\infty} \sum_{m=-l}^l c_{lm} Y_l^m(\vec{v})$$



$$K_l(b) Y_l^m(\vec{u}) = \int_{\vec{v} \in S^2} F(b, \vec{u}, \vec{v}) Y_l^m(\vec{v}) d\vec{v}$$


$$E(b, \vec{u}) = \sum_{l=0, \text{even}}^{\infty} \sum_{m=-l}^l c_{lm} K_l(b) Y_l^m(\vec{u})$$

- With  $Y_l^m(\vec{v})$  are the real **Spherical Harmonics** (SH) functions
-

# Spherical Mean Technique

---

$$E(b, \vec{\mathbf{u}}) = \sum_{l=0, \text{even}}^{\infty} \sum_{m=-l}^l c_{lm} K_l(b) Y_l^m(\vec{\mathbf{u}})$$


$$\begin{aligned} \bar{E}(b) &= \frac{1}{4\pi} \int_{\vec{\mathbf{u}} \in \mathcal{S}^2} E(b, \vec{\mathbf{u}}) d\vec{\mathbf{u}} \\ &= \frac{1}{4\pi} K_0(b) \end{aligned}$$

- The **mean** of the signal depends **only** on the **microstructural kernel** and not on the **fiber orientation**<sup>7,9,10</sup>
-

# Aims

---

In this work:

- We will compare the neurite density estimated using **three** different Multi-Compartment models
  - We evaluate its **inter-subject reproducibility**
  - We evaluate the effect of the other model **parameters** on its estimation in-vivo
-



# Multi-Compartment models

---

**NODDI-SH**

$$E(\mathbf{b}) = (1 - \nu_{csf})(E_{ia}(\mathbf{b}, \lambda_{\parallel}^{ia}) + \nu_{ea}E_{ea}(\mathbf{b}, \lambda_{\parallel}^{ea}, \lambda_{\perp}^{ea})) + \nu_{csf}E_{csf}(b)$$

$$\lambda_{\parallel}^{ia} = \lambda_{\parallel}^{ea} = 1.7 \cdot 10^{-3} \text{ mm}^2/\text{s}$$

$$\lambda_{\perp}^{ea} = \lambda_{\parallel}^{ea} \frac{\nu_{ea}}{\nu_{ia} + \nu_{ea}}$$



**BS-SH**

$$E(\mathbf{b}) = \nu_{ia}E_{ia}(\mathbf{b}, \lambda_{\parallel}^{ia}) + \nu_{ea}E_{ea}(\mathbf{b}, \lambda_{\parallel}^{ea}, \lambda_{\perp}^{ea})$$

$$\lambda_{\parallel}^{ia} = 1.7 \cdot 10^{-3} \text{ mm}^2/\text{s}$$

$$\lambda_{\parallel}^{ea} = \lambda_{\perp}^{ea}$$



**MC-MDI**

$$E(\mathbf{b}) = \nu_{ia}E_{ia}(\mathbf{b}, \lambda_{\parallel}^{ia}) + \nu_{ea}E_{ea}(\mathbf{b}, \lambda_{\parallel}^{ea}, \lambda_{\perp}^{ea})$$

$$\lambda_{\parallel}^{ia} = \lambda_{\parallel}^{ea}$$

$$\lambda_{\perp}^{ea} = \lambda_{\parallel}^{ea}(1 - \nu_{ia})$$



# Human Connectome Project (HCP)

---

- We considered 10 subjects of the **Human Connectome Project**<sup>8</sup>
- b-values = [1000, 2000, 3000] s/mm<sup>2</sup>
- 90 gradients per shell plus 18 b 0
- $\Delta = 43.1\text{ms}$  and  $\delta = 10.6\text{ms}$



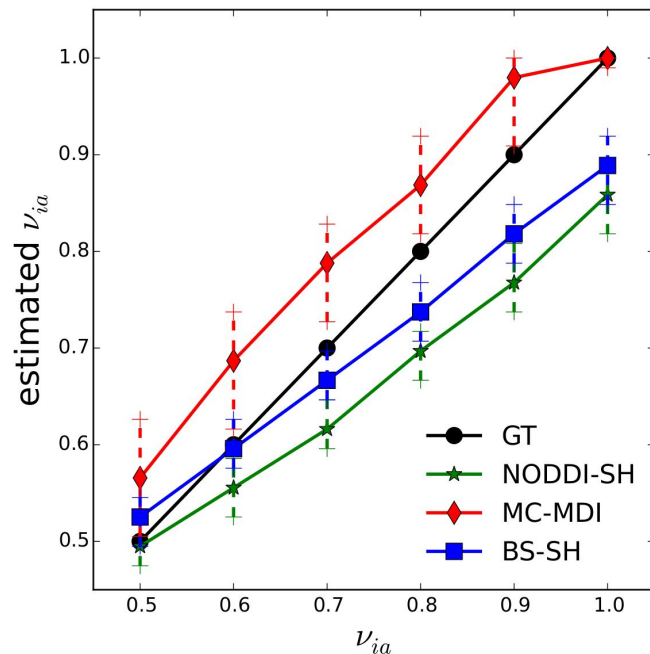
**CONNECTOME**  
COORDINATION FACILITY

---

# Synthetic data Results (from MICCAI 2017)

Our previous results<sup>7</sup> on **synthetic data** shown that:

- NODDI-SH and BS-SH tend to **underestimate** the neurite density
- MC-MDI tends to **overestimate** it

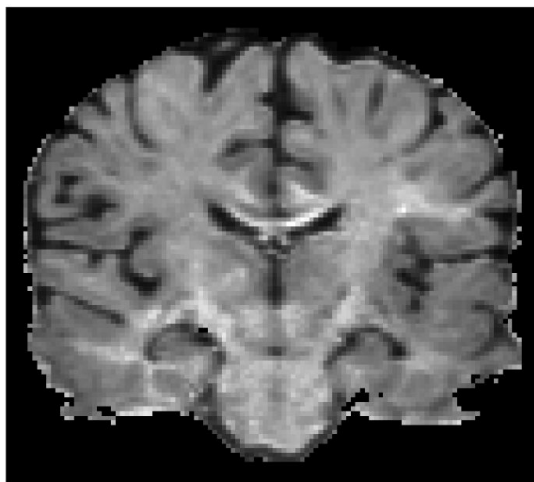


Zucchelli, M., Descoteaux, M., Menegaz, G. (2017). Proceedings of MICCAI, Workshop on Computational Diffusion MRI (CDMRI), Canada.

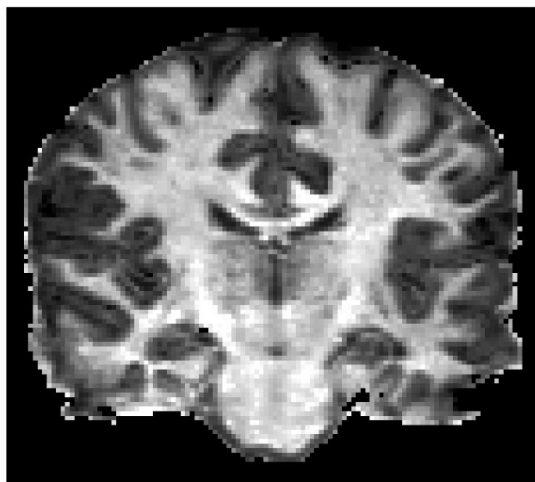
# HCP Results

---

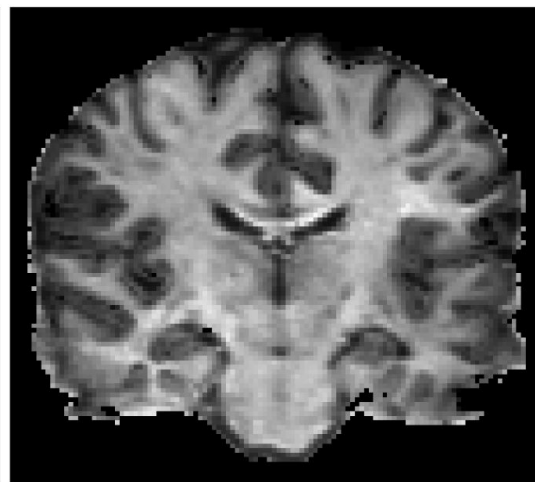
NODDI-SH



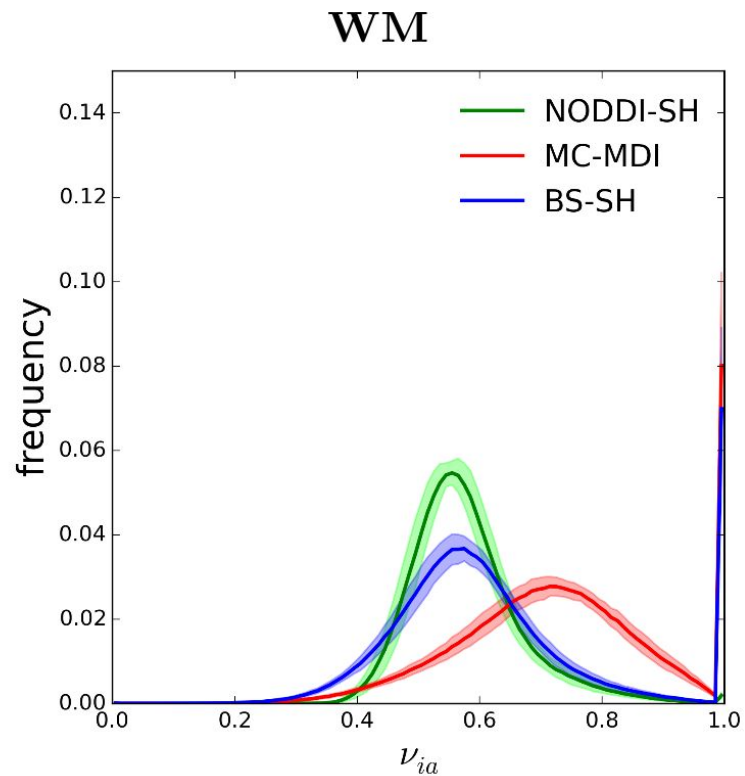
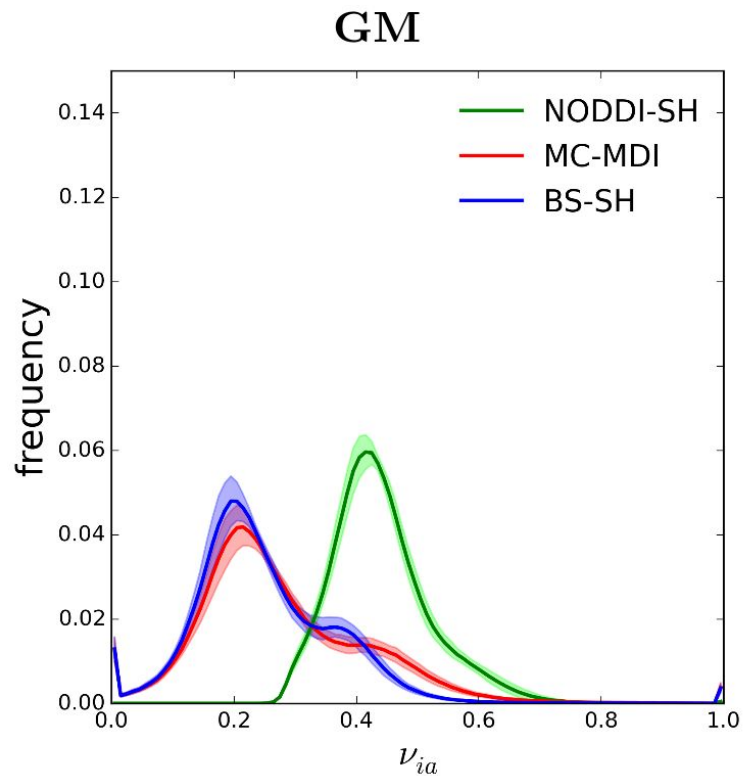
MC-MDI



BS-SH



# HCP Results



# Conclusions

---

- **Neurite density** has a well defined numerical range and it is **stable** across healthy subjects
  - However, its values strongly depend on the **choice of the model** used to calculate it
  - Our results suggest that it could potentially be used as a **feature** to discriminate between healthy brains and pathological conditions
  - However, it is extremely important to keep in mind that its values are only proportional to the **real underlying neural density** and to compare it only with studies that use exactly the same model for its estimation
-

# Acknowledgements

---

- *This work has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (ERC Advanced Grant agreement No 694665 : CoBCoM - Computational Brain Connectivity Mapping)*
  - *Data were provided by the Human Connectome Project, WU-Minn Consortium(Principal Investigators: David Van Essen and Kamil Ugurbil; 1U54MH091657)funded by the 16 NIH Institutes and Centers that support the NIH Blueprint forNeuroscience Research; and by the McDonnell Center for Systems Neuroscience at Washington University.*
-

# References

---

1. Jespersen, S.N., et. al (2010) : *Neurite density from magnetic resonance diffusion measurements at ultrahigh field: Comparison with light microscopy and electron microscopy. NeuroImage* 49(1) 205 – 216
  2. Zhang, H., et. al. (2012). *NODDI: practical in vivo neurite orientation dispersion and density imaging of the human brain. Neuroimage*, 61(4), 1000-1016.
  3. Lampinen, B., et. al. (2017). *Neurite density imaging versus imaging of microscopic anisotropy in diffusion MRI: A model comparison using spherical tensor encoding. NeuroImage*, 147, 517-531.
  4. Novikov, D. S., et. al (2016). *Quantifying brain microstructure with diffusion MRI: Theory and parameter estimation. arXiv preprint arXiv:1612.02059.*
  5. Reisert, M., et. al. (2017). *Disentangling micro from mesostructure by diffusion MRI: A Bayesian approach. NeuroImage*, 147, 964-975.
  6. Behrens, T. E., et. al. (2003). *Characterization and propagation of uncertainty in diffusion weighted MR imaging. Magnetic resonance in medicine*, 50(5), 1077-1088.
  7. Zucchelli, M., Descoteaux, M., Menegaz, G. (2017), *A generalized SMT-based framework for Diffusion MRI microstructural model estimation. Proceedings of MICCAI, Workshop on Computational Diffusion MRI (CDMRI)"* , Quebec City, Canada.
  8. Sotiropoulos, S.N., et al. (2013): *Advances in diffusion MRI acquisition and processing in the human connectome project. NeuroImage* 80 125–143
  9. Kaden, E., et. al. (2016). *Multi-compartment microscopic diffusion imaging. NeuroImage*, 139, 346-359.
  10. Zucchelli, M., Descoteaux, M., & Menegaz, G. (2017). *NODDI-SH: a computational efficient NODDI extension for fODF estimation in diffusion MRI. arXiv preprint arXiv:1708.08999.*
-