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

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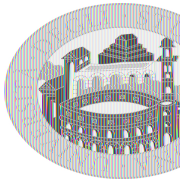

Investigating Diffusion-MRI based neurite density estimation model dependency: an in-vivo study on the HCP dataset

Mauro Zucchelli[1,3], Maxime Descoteaux[2], and Gloria Menegaz[1]

[1]University of Verona (Italy), [2]University of Sherbrooke (Canada), [3]INRIA, Sophia Antipolis-Méditerranée (France)

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Time: 09:15, 18th June
Number: 3235
Computer N°: 41

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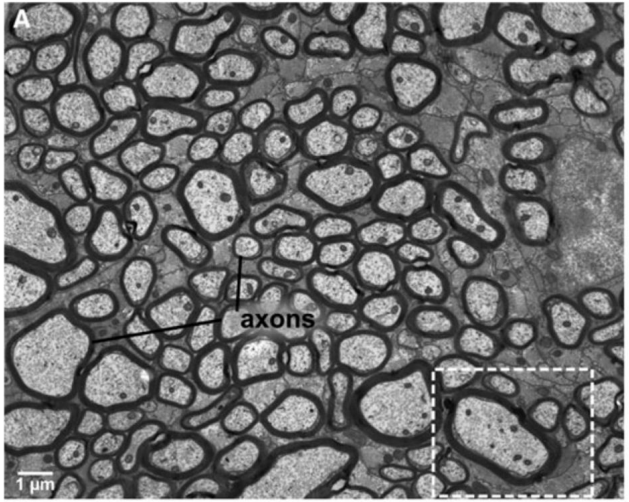
Neurite Density and Diffusion MRI

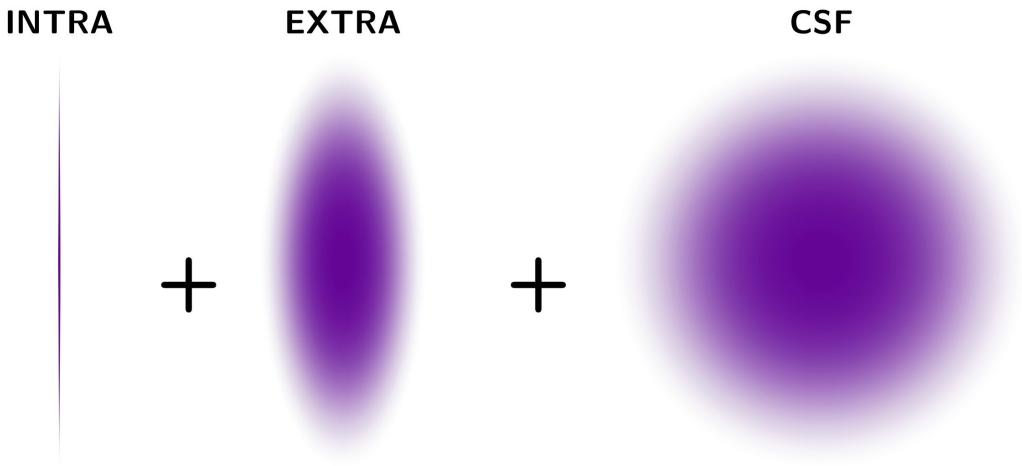
- **Neurite density**[1,2,3,4,5] is one of the most promising microstructural features that can be estimated from **Diffusion-MRI** multi-shell data
- Recent years have seen a proliferation of **Multi-Compartment models** developed to estimate the neurite density



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***



Neurite Density and Diffusion MRI

- Neurite density can be calculated from Multi-Compartment models as the **intra-axonal volume fraction** (v_{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**[1,2,3,4,5,6,7,9,10] 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**)

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

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

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

Spherical Mean Technique

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

$$\overline{E}(b) = \frac{1}{4\pi} \int_{\vec{\mathbf{u}} \in \mathcal{S}^2} E(b,\vec{\mathbf{u}}) d\vec{\mathbf{u}}$$

$$= \frac{1}{4\pi} K_0(b)$$

- The **mean** of the signal depends **only** on the **microstructural kernel** and not on the **fiber orientation**[7,9,10]

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

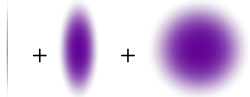
Multi-Compartment models

NODDI-SH

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

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

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



BS-SH

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

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

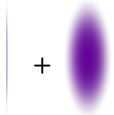
$$\lambda_{\parallel}^{ea} = \lambda_{\perp}^{ea}$$

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)

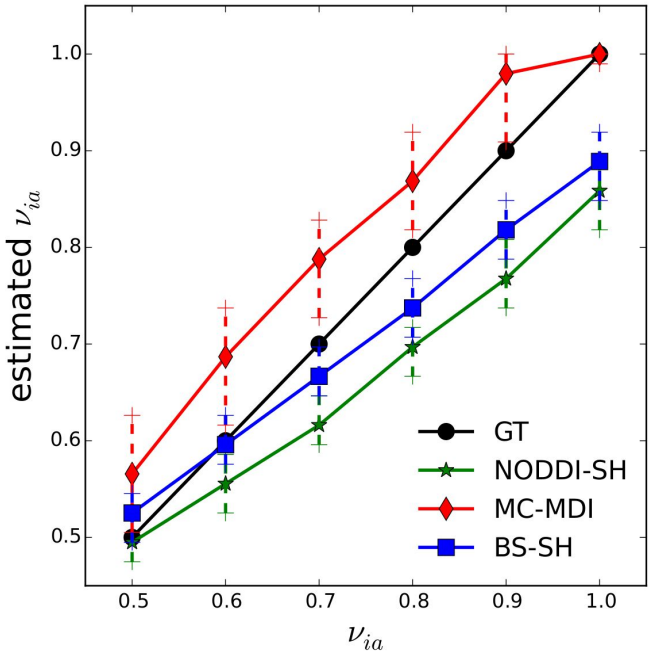
- We considered 10 subjects of the **Human Connectome Project**[8]
- b-values = [1000, 2000, 3000] s/mm^2
- 90 gradients per shell plus 18 b 0
- Δ = 43.1ms and δ = 10.6ms

CONNECTOME
COORDINATION FACILITY

Synthetic data Results (from MICCAI 2017)

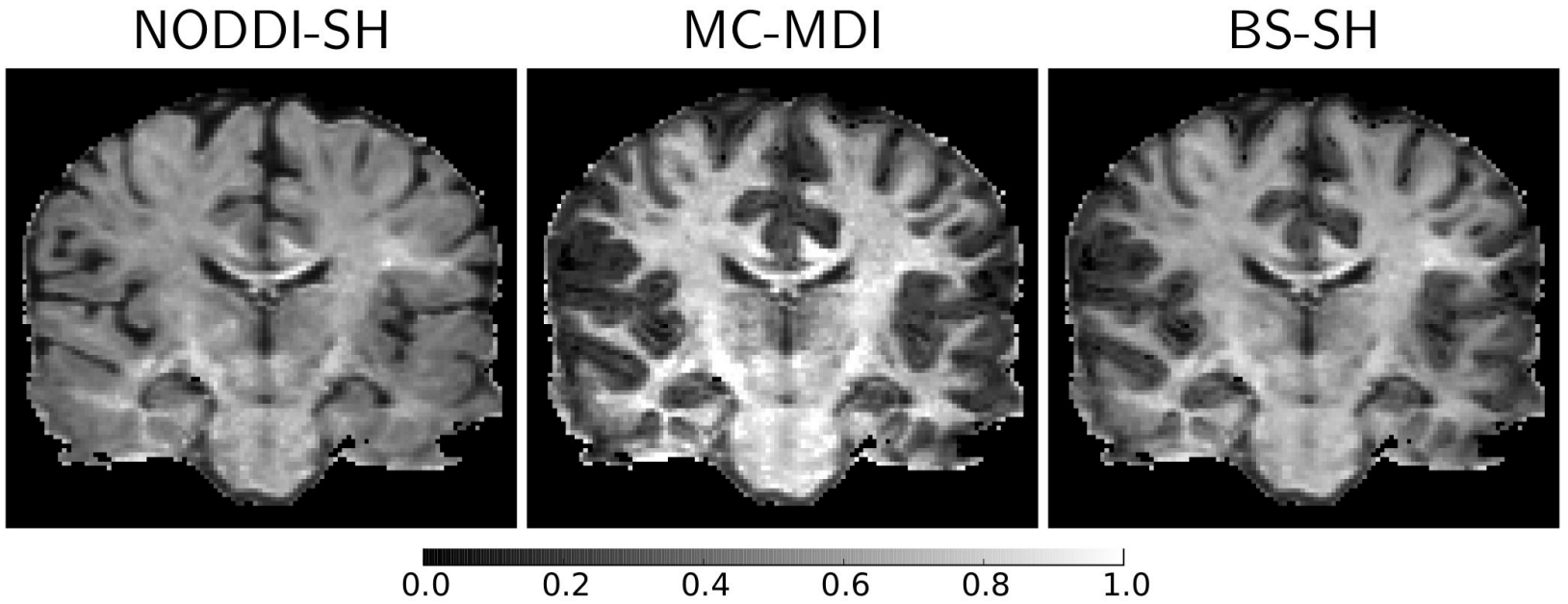
Our previous results[7] on **synthetic data** shown that:

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

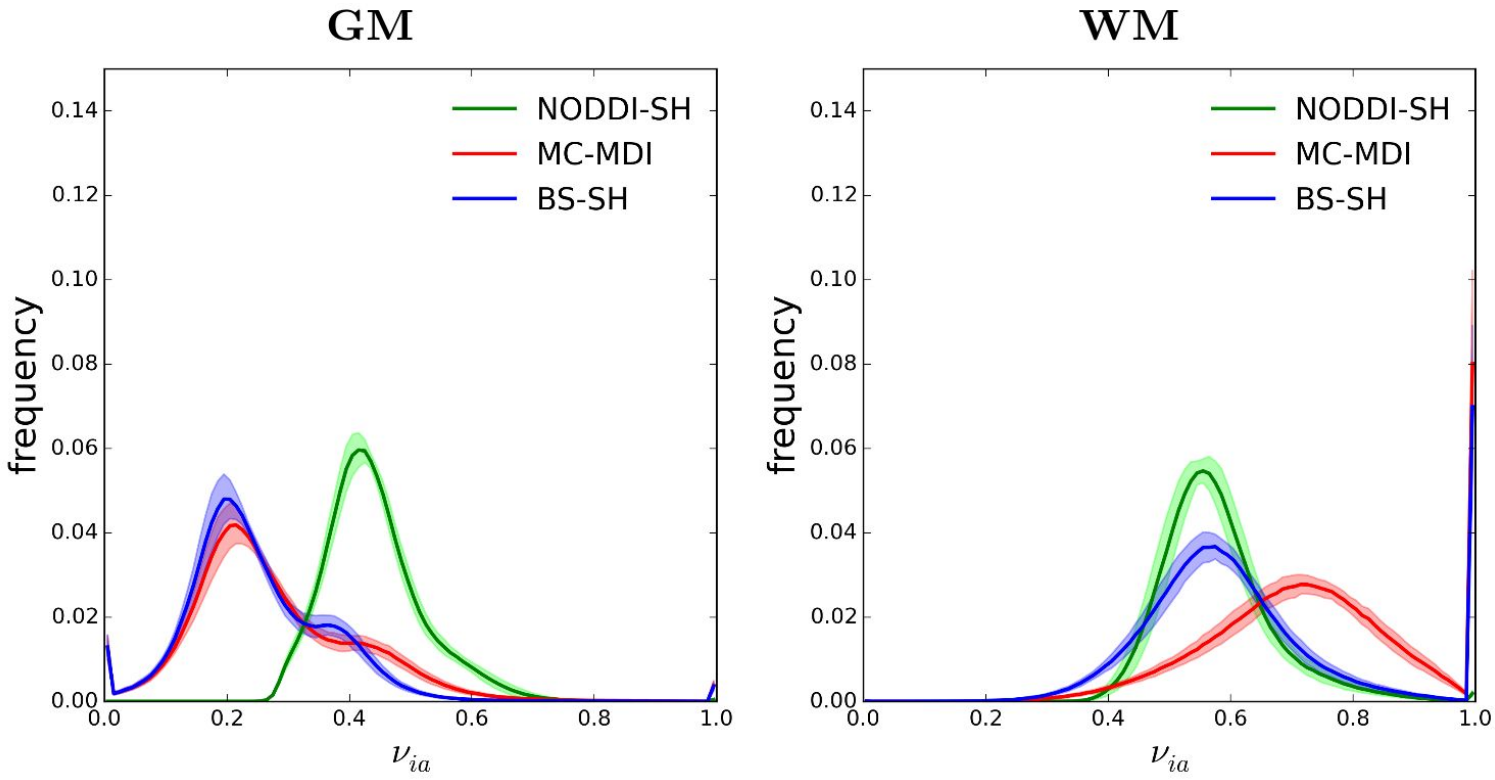


Zucchelli, M., Descoteaux, M., Menegaz, G. (2017). Proceedings of MICCAI, Workshop on Computational Diffusion MRI (CDMRI)", Canada.

HCP Results



HCP Results


GM
WM
NODDI-SH
MC-MDI
BS-SH
frequency
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0.0
0.2
0.4
0.6
0.8
1.0
ν_{ia}

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

Aknowledgements

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- *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.*

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