



Multi-Fascicle Models for Population Studies of the Brain Microstructure

Soutenance de thèse Louvain-la-Neuve, October 2013

Maxime Taquet







Disconnection syndromes and other disorders are thought to affect the connections in the brain



The microstructure underpins connectivity





Anisotropic restricted diffusion





Isotropic restricted diffusion



Astrocyte	
Axon	*
Myelin	
Microglia	



Anisotropic hindered diffusion











If there is no exchange of water molecules between the different compartments



Fraction of water molecules in each compartment

restricted in axons unrestricted (GM, CSF) restricted in glial cells hindered in extra-axonal space

30%

46%

4%

20%

Images of the brain microstructure contain a model in each voxel

The models in different voxels have different parameters



Axons travel in fascicles



In most voxels, several fascicles cross each other



At typical resolution, 60-90% of the brain voxels contain crossing fascicles

Jeurissen et al., 2012

In most voxels, several fascicles cross each other

Multi-Fascicle models of the

brain microstructure

Fraction of water molecules in each compartment





Myelin injury is translated in a decreased axial diffusivity

Axon injury



Multi-Fascicle models of the

brain microstructure



Song et al., Neuroimage 2003

Population studies of the brain microstructure from diffusion imaging



 Acquire
 Image: Sector and the secto

New assets and capabilities to conduct population studies of the brain microstructure

I. Selection of the appropriate model

2. Registration and atlas construction

3. Statistical analysis of microstructure

4. Estimation from single b-value data

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Given a set of data, we ought to know what model can be reliably estimated

Misses crossing fascicles



Given a set of data, we ought to know what model can be reliably estimated

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We proposed that the appropriate model best generalizes to new data not included in the estimation



→ Compute the generalization error
632 Bootstrap estimator











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Registration and atlas construction are at the heart of population studies

Population

Registration

Atlas



Registration and atlasing require specific operations

Interpolation

Registration and atlasing require specific operations

Interpolation

Averaging



Registration and atlasing require specific operations

Interpolation

Averaging



Registration and atlasing require specific operations

Interpolation Averaging Smoothing



Registration and atlasing require specific operations

Interpolation

Averaging Smoothing Similarity metric







Diffusivities differ between subjects

We proposed a mathematical framework that includes image analysis operators for multi-fascicle models



Minimization of the cumulative differential relative entropy

We proposed a mathematical framework that includes image analysis operators for multi-fascicle models

Generalized correlation coefficient

$$\rho(R,S) = \left\langle \frac{R - \mu_R}{||R - \mu_R||}, \frac{S - \mu_S}{||S - \mu_R||} \right\rangle$$

$$\rho(R,S) = m\left(\frac{R - m(R,T)T}{n_m(R - m(R,T)T)}, \frac{S - m(S,T)T}{n_m(S - m(S,T)T)}\right)$$

$$m(R,S) = \sum_{x \in \Omega} \max_{\pi} \sum_{i=1}^{N} f_i g_{\pi(i)} \left\langle \log \mathbf{D}_i^R, \log \mathbf{D}_{\pi(i)}^S \right\rangle$$

invariant under linear transformations of the log-eigenvalues Taquet et al., IEEE TMI, in press, 2013

Experiment I: Interpolation Error



Our approach

Multi-channel -



Experiment I: Interpolation Error

Experiment 2: Scan-Rescan to test the similarity metric



Saliency maps





Experiment 2: Scan-Rescan to test the similarity metric

Our metric leads to significantly smaller registration errors



Accuracy [# voxels]

Experiment 3: 1,440 synthetic field registrations Our method performs significantly better



Our framework enables the construction of a multi-fascicle atlas



are well represented in the atlas Taquet et al., IEEE TMI, in press, 2013 New assets and capabilities to conduct population studies of the brain microstructure

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Features of the brain microstructure may relate to a particular fascicle or to the surrounding volume



We proposed a system of two methods for the statistical analysis of microstructural features

Fascicle-based spatial statistics

for properties related to fascicles

I. tractography

2. interpolation

3. selection

4. cluster-based statistics



We proposed a system of two methods for the statistical analysis of microstructural features

Isotropic diffusion analysis

for properties related to volume

I. Feature extraction



2. Feature transformation

 $l_{\rm iso} = {\rm logit} f_{\rm iso}$

3. cluster-based statistics



Our system detects differences between healthy controls and children with autism

IDA reveals regions with abnormally high fraction of molecules diffusing freely, mostly in the dorsal language pathway.

p=.05

p=0

This finding may point to the hypothesis that autism results from an autoimmune response.

Our system detects differences between healthy controls and children with autism

FBSS reveals few clusters of significantly lower fractional anisotropy along the dorsal language pathway.









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Multi-fascicle models cannot be directly estimated from data at a single b-value



Single gradient shell

The problem is ill-posed

All those models produce the same signal



This may result in a waste of effort





Age

Images and neuropsychological data from 1,400 children



Not all models are as likely given the known anatomy



We proposed to incorporate prior information from other subjects scanned at multiple b-values



Each voxel of the atlas contains a parametric distribution of the parameters



Taquet et al., MICCAI, 2013

We proposed to incorporate prior information from other subjects scanned at multiple b-values



Each voxel of the atlas contains a parametric distribution of the parameters





 $p(\boldsymbol{f}, \boldsymbol{D} | \text{Data}) \propto p(\text{Data} | \boldsymbol{f}, \boldsymbol{D}) p(\boldsymbol{f}, \boldsymbol{D})$ Likelihood

 $p(\boldsymbol{f}, \boldsymbol{D})$ is informed by the atlas

p(f, D) = p(f)p(D)Dirichlet

Matrix-variate Gaussian

Taquet et al., MICCAI, 2013

The population-informed prior significantly improves the accuracy of the estimation

Experiment I: Synthetic data



The population-informed prior significantly improves the accuracy of the estimation

Experiment I: Synthetic data



The population-informed prior significantly improves the accuracy of the estimation

Experiment 2: In-vivo data



Detected group differences are remarkably close to those found with multiple b-values

With multiple b-values

With a single b-value



p=.05

p=0

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Thank you

Journals

Taquet et al., Neuroimage (under review) Taquet et al., IEEE TMI, 2013 Peters*, Taquet* et al., Future Neurology, 2013 Taquet and Peters, Médecine/Sciences, 2013 Peters*, Taquet*, et al., BMC Medicine, 2013 Peer-reviewed conference abstracts Taquet et al., OHBM 2013 Taquet et al., ISMRM 2013 Scherrer et al., ISMRM 2013 Peters*, Taquet* et al., American Acad. of Neurology 2013 Peters*, Taquet* et al. Child Neurology Society, 2012 Taquet et al., CAOS 2010

* Equal contributions

Full-length peer-reviewed conference papers Taquet et al., MICCAI 2013 Scherrer et al., MICCAI 2013 Scherrer*, Taquet* et al., IPMI 2013 Taquet et al., MICCAI 2012 Taquet et al., IEEE ISBI 2012 Taquet et al., IEEE MMBIA 2012 Taquet et al., MICCAI 2011 Taquet et al., IEEE ICIP 2011 Taquet et al., CTIC 2010 Taquet, IEEE Melecon 2010



