## Uncertainties in Diffusion MRI

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### Collaborators



### Ingrid (3 months) also helped!







- **DWI hypothesis:** Water diffuses *along* fibers, not across
- ► Typical DWI pipeline:
  - Local modelling: Estimate "fiber orientation distribution function" (fODF) from data
  - Global modelling: Integrate local models to obtain long-range connectivity



Figure: Field of diffusion tensors estimated from data.

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Figure: Field of fODFs estimated via constrained spherical deconvolution.

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Figure: Estimate of white-matter fiber by integrating the fODF field.

- Reflection symmetric probability distribution on S<sup>2</sup> modelling probability of tangential white matter bundle
- E.g. used for quantifying microstructural properties
- Does quantify uncertainty but in an ad hoc way, based on a single noisy measurement
- Limitations: Angular resolution, scale of measurement vs anatomy, model assumptions, ...



#### Geometrize the brain:

Interpolated diffusion tensors define Riemannian geometry; **Shortest paths** = estimates of white matter trajectories (O'Donnel et al'02; Lenglet et al'04)



A local distance is estimated from a Gaussian approximation to the diffusion process.



#### Shortest paths are found by optimization

Shortest paths = 
$$\arg\min_{\mathbf{c}} \int_{0}^{1} \sqrt{\dot{\mathbf{c}}(t)^{\intercal} \mathbf{M}(\mathbf{c}(t)) \dot{\mathbf{c}}(t)} dt$$

Such paths are solutions to the differential equation

$$\begin{split} \ddot{c}_d(t) &= f_d(t, \mathbf{c}, \dot{\mathbf{c}}) = -\boldsymbol{\Gamma}_d^{\mathsf{T}} \cdot \left( \dot{\mathbf{c}}(t) \otimes \dot{\mathbf{c}}(t) \right), \\ \boldsymbol{\Gamma}_d &= \frac{1}{2} \sum_{k=1}^{D} \left[ \mathbf{M}_{\mathbf{c}(t)}^{-1} \right]_{d,k} \left( \frac{\partial \operatorname{vec} \mathbf{M}_{\mathbf{p}}}{\partial p_k} \right)_{\mathbf{p} = \mathbf{c}(t)} \end{split}$$

which can be solved numerically.

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Riemannian shortest paths are solutions to a 2nd order diff-EQ Numerical uncertainty quantified by solving the diff-EQ it using GP regression (Schober et al, MICCAl'14)



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#### Incorporate measurement uncertainty:

Modern DWI has "high" angular resolution; DTI requires far less Bootstrap the data to obtain uncertain diffusion tensors = stochastic Riemannian metric

Obtain uncertain GP estimates of white matter tracts solving the geodesic diff-EQ using GP regression (Hauberg et al, MICCAI'15)



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#### A number of problems remain:

- \* Propagation of uncertainty with distance to endpoints: A ProbNum problem
- \* Proper modelling of local uncertainty
- \* Propagation of uncertainty throughout imaging pipeline
- \* More flexible fODF models; avoid inflated uncertainty due to poor model fit
- \* Uncertain fiber tracking (not shortest-path tractography)



### Uncertainties in population modelling

State-of-the-art in population modelling is to represent the tract by a fixed prototype and perform population analysis on scalar properties measured along the prototype.



Figure: O'Donnel et al, NeuroImage'09.

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Figure: Garyfalldis et al, Front Neurosci'12

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Ignoring uncertainty in population modelling is a problem

- The more clinical your paper is, the more likely you are to have to support your claims by p-values (my experience)
- Ignoring uncertainty can lead to incorrect "significant" differences



Conclusion: If your final output includes an uncertainty, then it needs to be propagated from the uncertainty of your "data"

### Back to population analysis of white matter tracts

- Different tracts are *not* independent observations of one phenomenon, they are highly dependent observations of highly dependent phenomena
- The noise is in the image. New observation = new image = unavailable.



#### Figure: By Thomas Schultz

# Learning from uncertain curves via Wasserstein distances between GPs (Mallasto and **F**, NeurIPS'17)

- Derived analytical approximations of Wasserstein distances, geodesics and barycenters for GPs via GD approximations
- Enables tractable distance-based learning



- Pros: Computationally tractable; resembles state-of-the-art methods without uncertainties
- **Cons:** Strict model assumptions; limited scope
- **Thus:** Very open problem



### Discussion and outlook

- Diffusion MRI offers a rich pool of problems in modelling, quantifying and communicating uncertainty
- We have first solutions based on GPs in global modelling and population analysis
- A wide range of open problems remain



Figure: From Garyfalldis et al, Front Neurosci'12