Spatiotemporal Modeling for Image Time Series with Appearance Change: Application to Early Brain Development

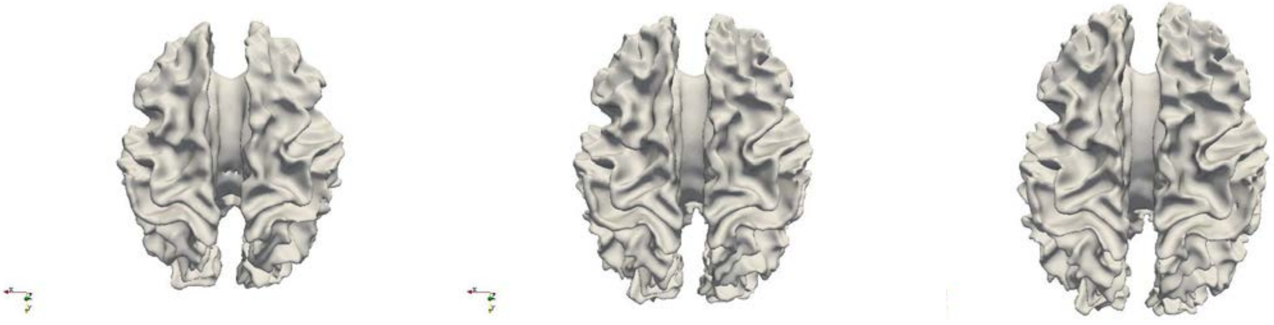
James Fishbaugh, Martin Styner, ..., Guido Gerig

MICCAI 2019, MFCA workshop, to appear Oct. 2019, LNCS Springer Verlag

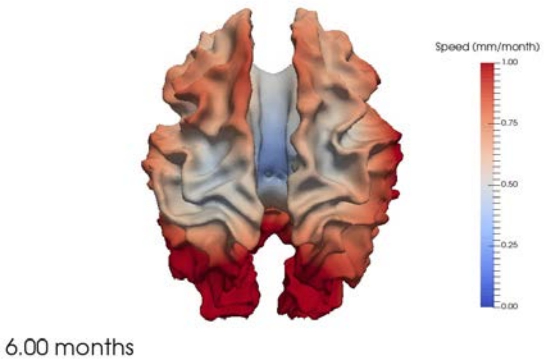
VISUALIZATION IMAGING AND DATA ANALYSIS CENTER

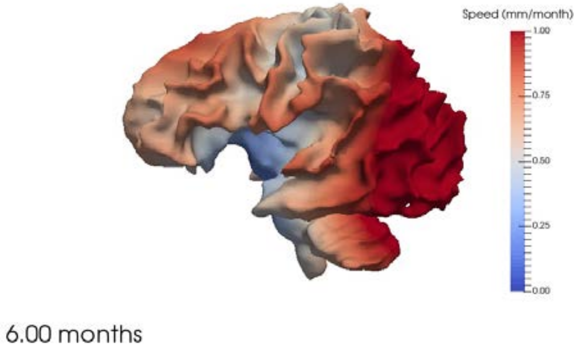
NYU TANDON SCHOOL OF ENGINEERING

Previous Work:
Shape regression from discrete time points



6 month | 12 month | 24 month



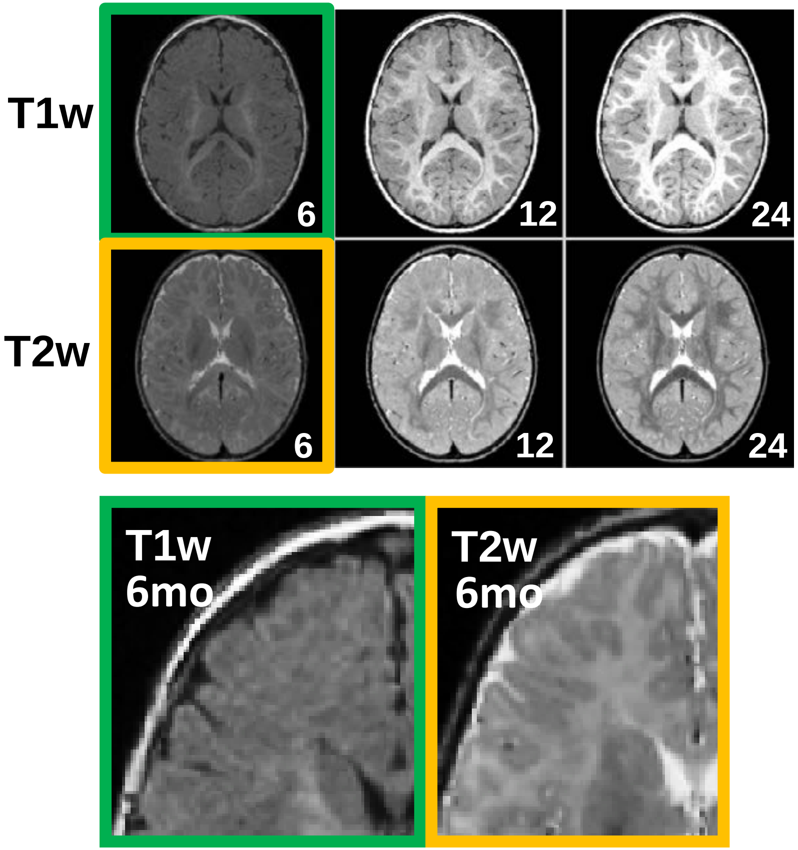


Geodesic Shape Regression: Growth of brain surface color-coded with local speed. Please notice rapid early development of occipital lobe (back of brain, dark red) due to early visual cortex maturation.

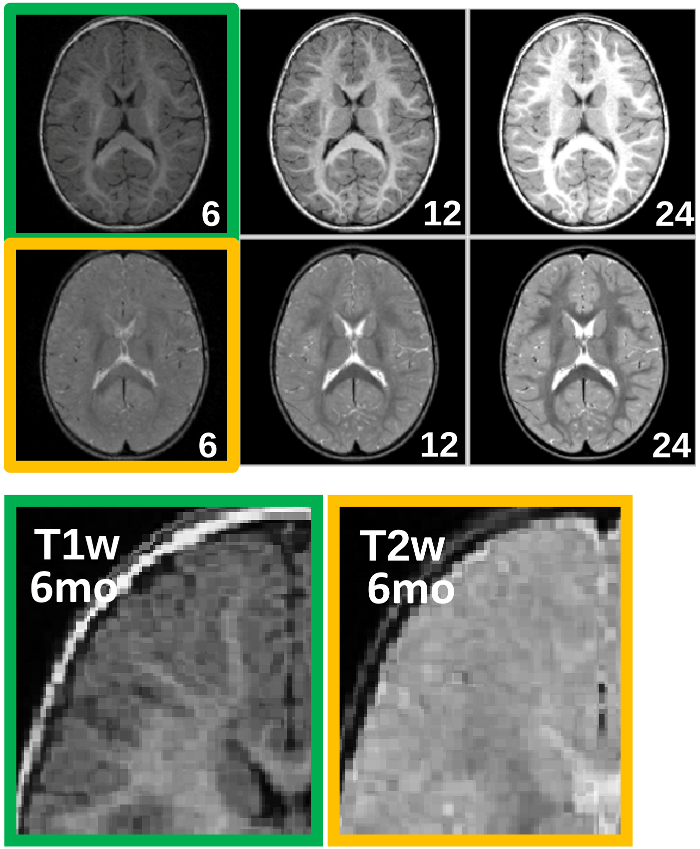
Fishbaugh et al., MedIA Elsevier 2017 / ISBI 2018

Motivation: “Growth/Maturation” seems also encoded in multi-modal MRI contrast

IBIS case 321541



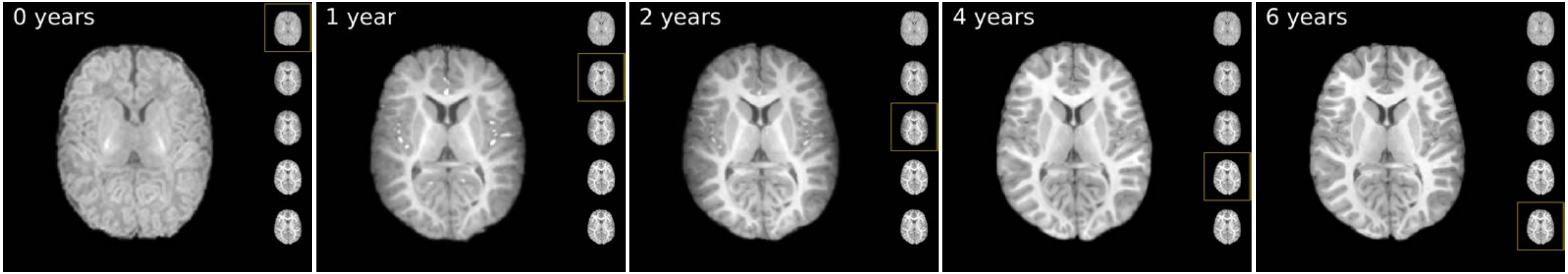
IBIS case xxxxxxxx

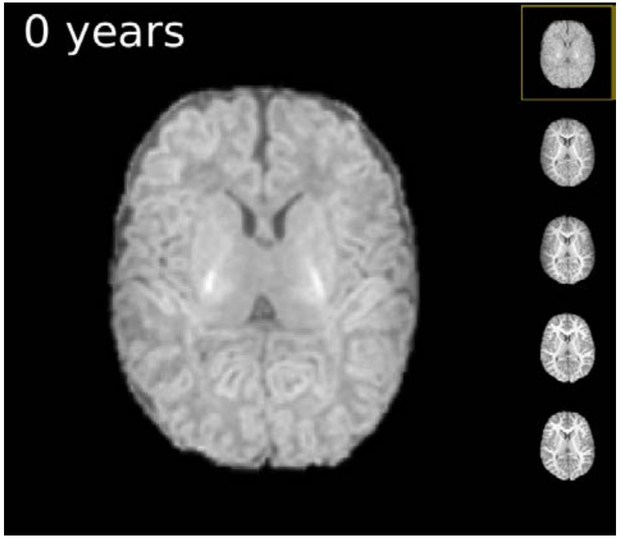


Observation: Two IBIS cases show different T1w/T2w contrast changes with different time trajectories.

Vardhan & IBIS et al., MICCAI 2017

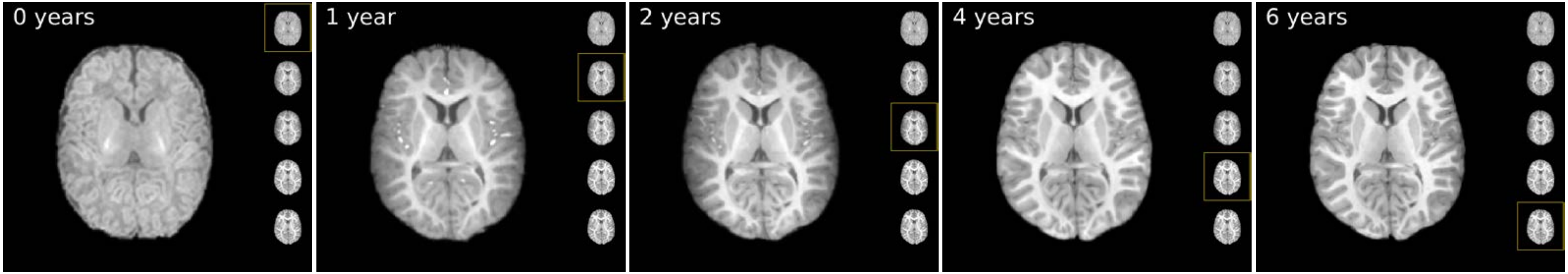
New: Regression of Structure & Appearance

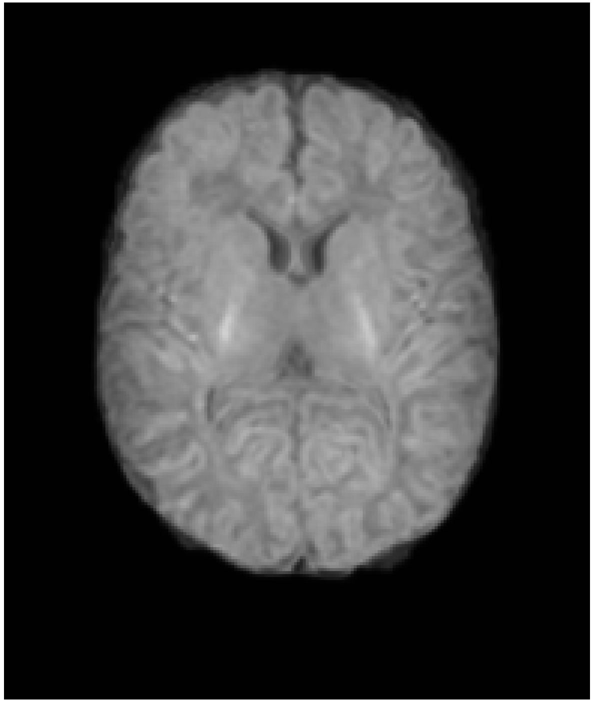




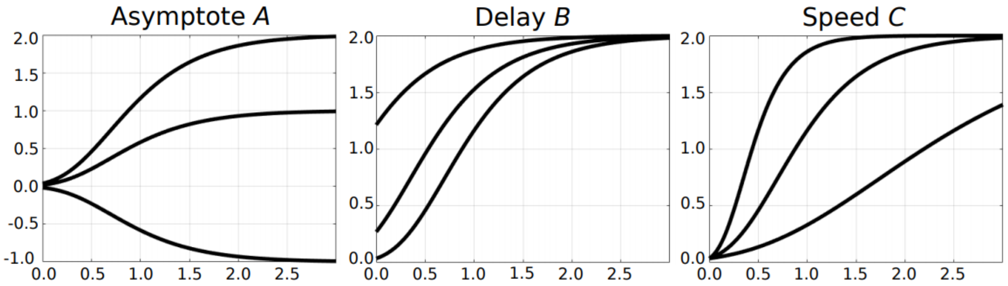
Challenges and Motivation:

- MRI represents anatomy & contrast.
- Co-registration of images with very different, locally varying contrasts is challenging.
- New approach: Joint modeling of growth trajectories of structure and appearance.





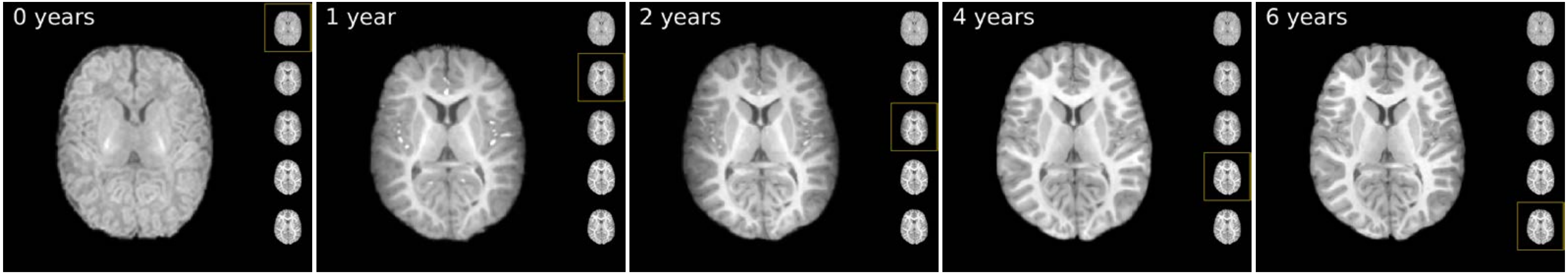
Spatiotemporal Model With Appearance Change

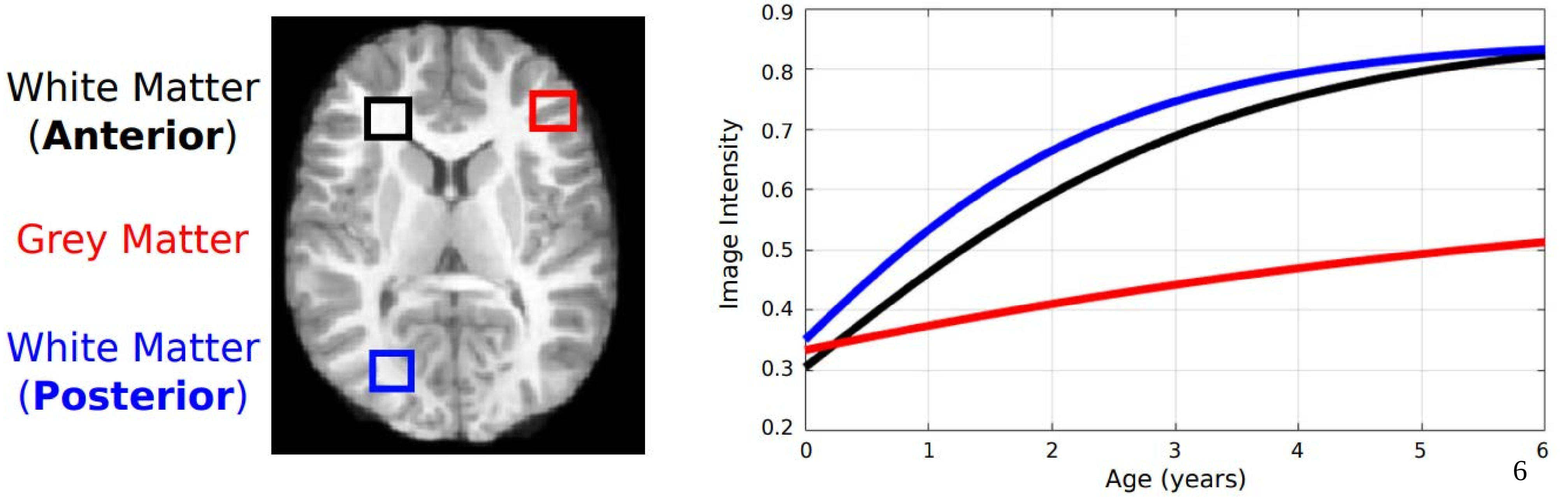


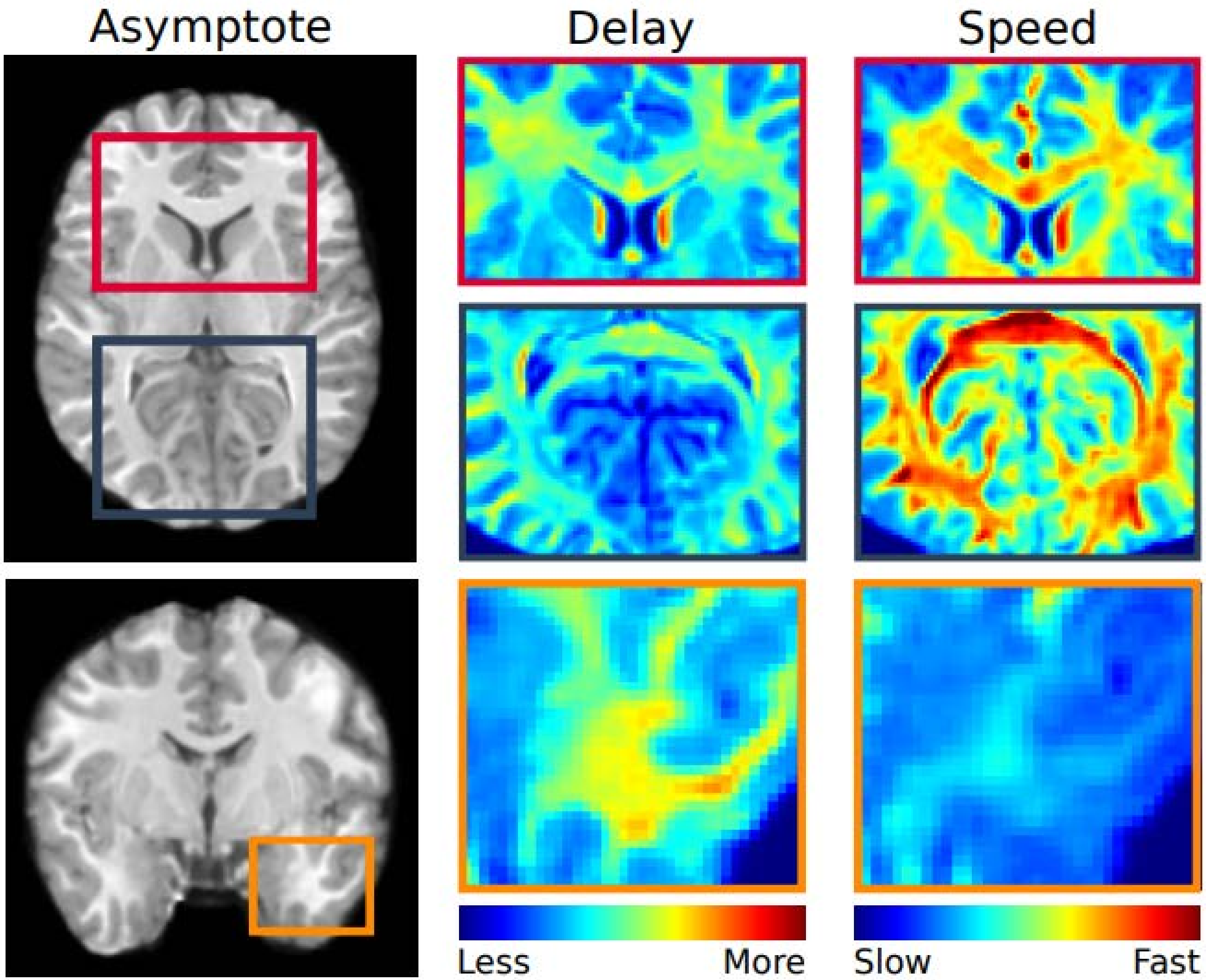
Gompertz model for intensity (Sadeghi, ISBI'13)

$$E(\boldsymbol{\alpha}(t), \mathbf{c}_0, A, B, C) = \left[\sum_{i=1}^{N_{obs}} \lambda_D \, d(\phi_{t_i}(\hat{\mathbf{I}}(t_0)), I_{t_i})^2 + \lambda_A \, d(\hat{\mathbf{I}}(t_i), I_{t_i})^2 \right]$$

$$+ \lambda_R \int_{t_0}^{T} ||\mathbf{a}(t)||_V^2 \, dt + \lambda_{TV} \; \mathrm{TV}(A, B, C)$$


0 years
1 year
2 years
4 years
6 years

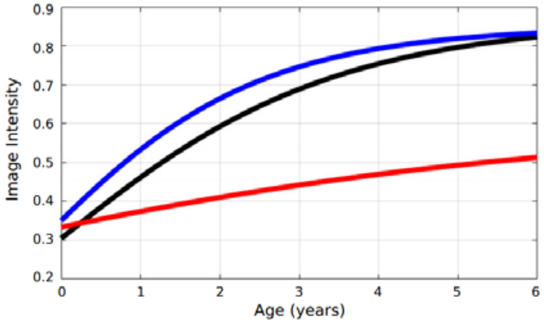

White Matter
(Anterior)
Grey Matter
White Matter
(Posterior)
Image Intensity
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
1
2
3
4
5
6
Age (years)



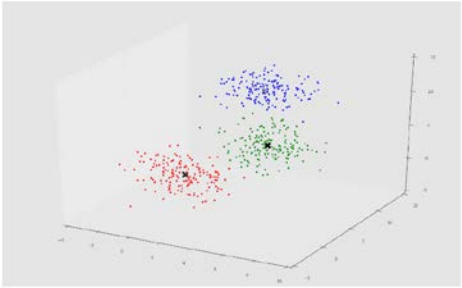
Appearance model provides additional information on tissue maturation:

- GM and WM show very different trajectories.
- Frontal, occipital and temporal lobes differ in delay and speed.

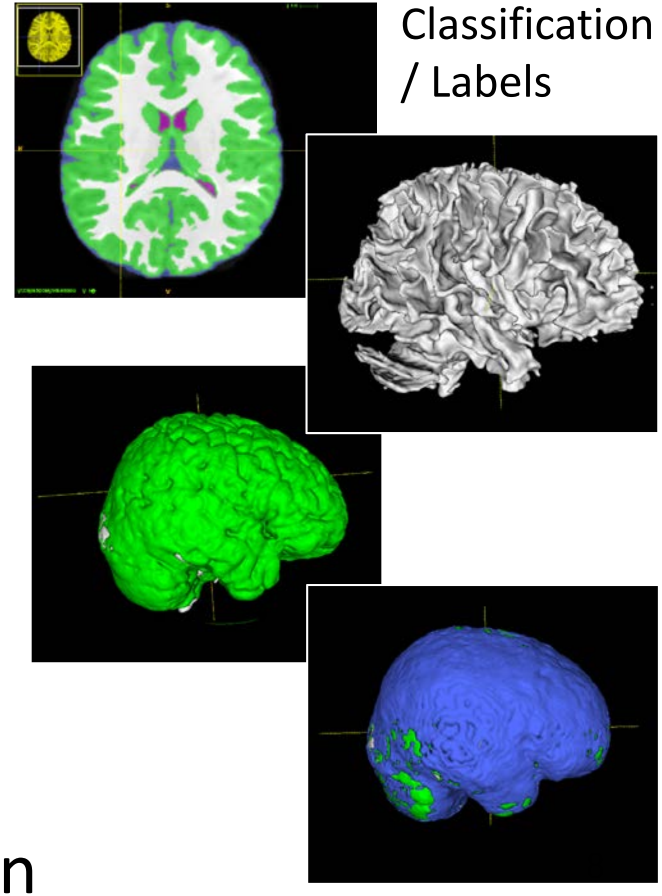
Data-driven segmentation



Voxel-wise appearance change



Clustering in A,B,C



Classification / Labels

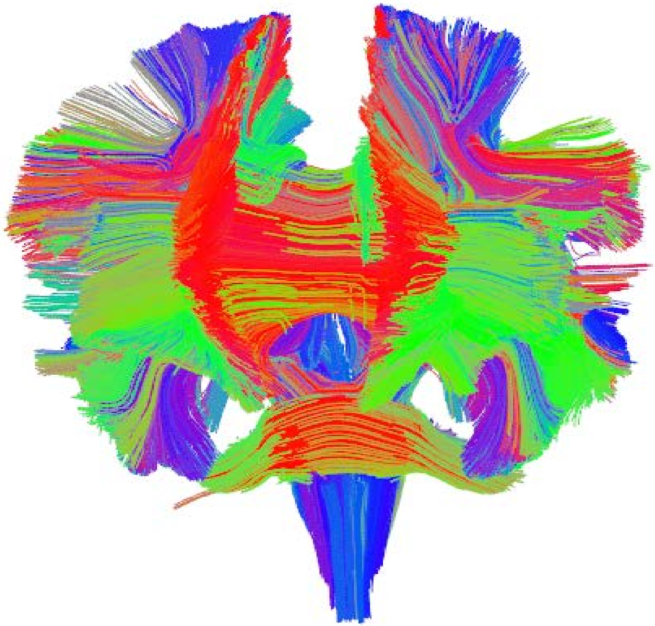
Work in progress:

Towards fully data-driven tissue segmentation

A framework to construct a longitudinal DW-MRI infant atlas based on mixed effects modeling of dODF coefficients

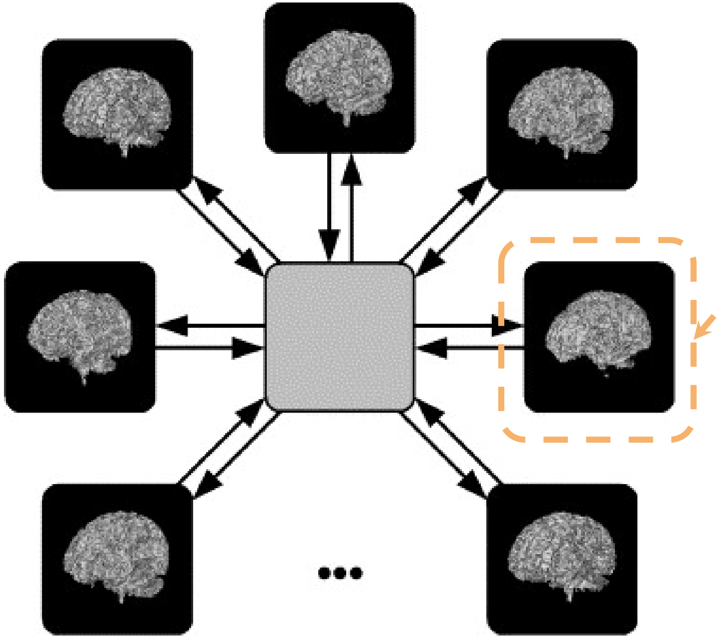
Heejong Kim, Martin Styner, Joseph Piven, and Guido Gerig

MICCAI CDMRI workshop, Oct. 2019

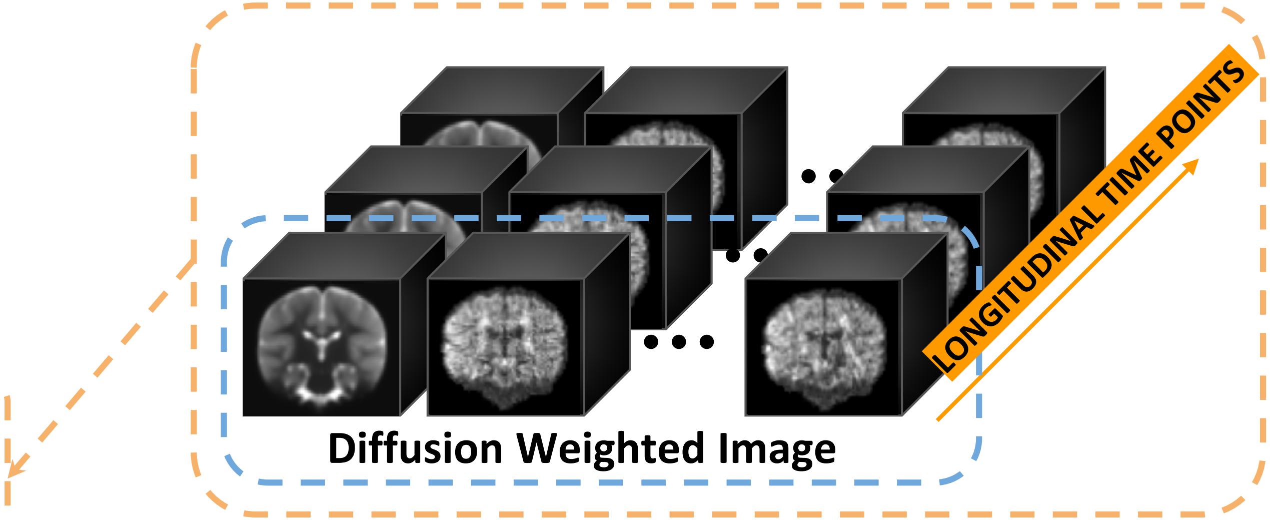


003 months

Goal: Framework to construct a *continuous* longitudinal DW-MRI infant atlas



Atlas construction framework on structural brain image*

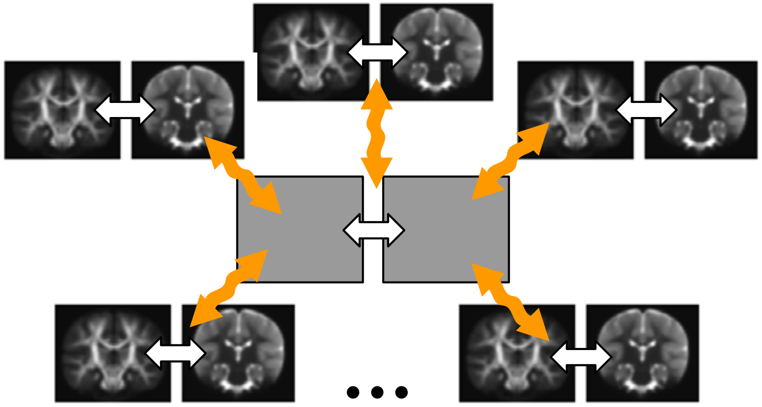


- Atlas building on longitudinal DW images is even more challenging because of **time changes**.

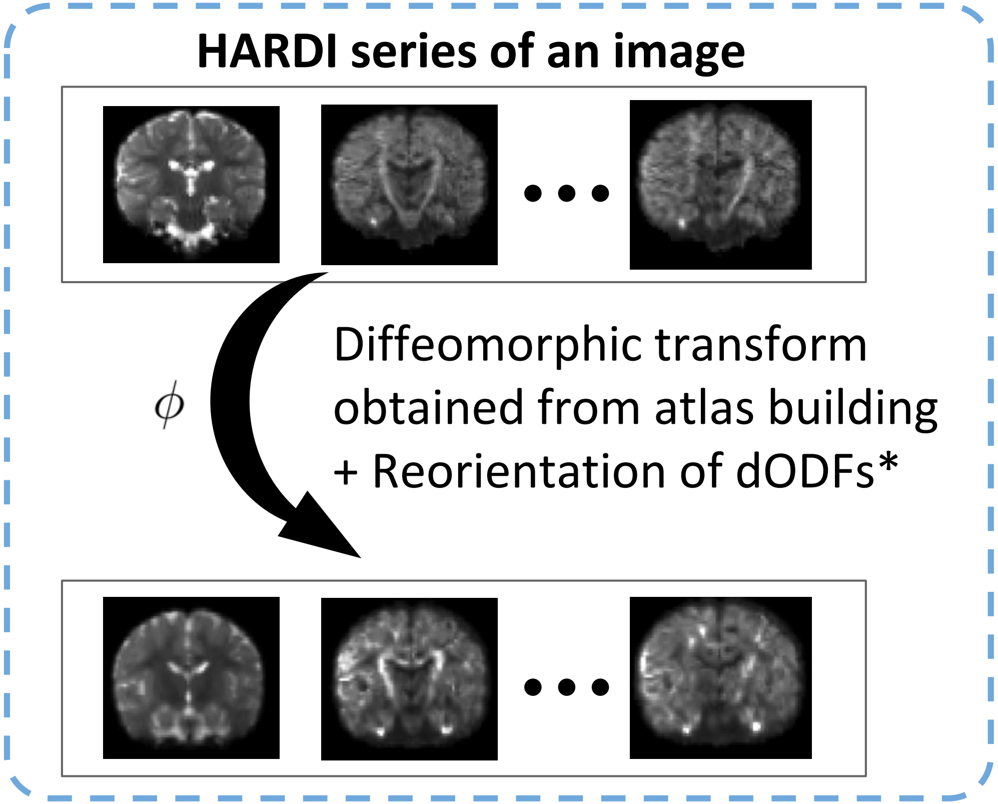
→ **Goal**: Propose a framework to construct a continuous longitudinal DW-MRI infant atlas

*Joshi, et al., NeuroImage, 2004 & Avants and Gee, NeuroImage 2004

Atlas Building Steps



Multivariate atlas construction framework (B0, FA)

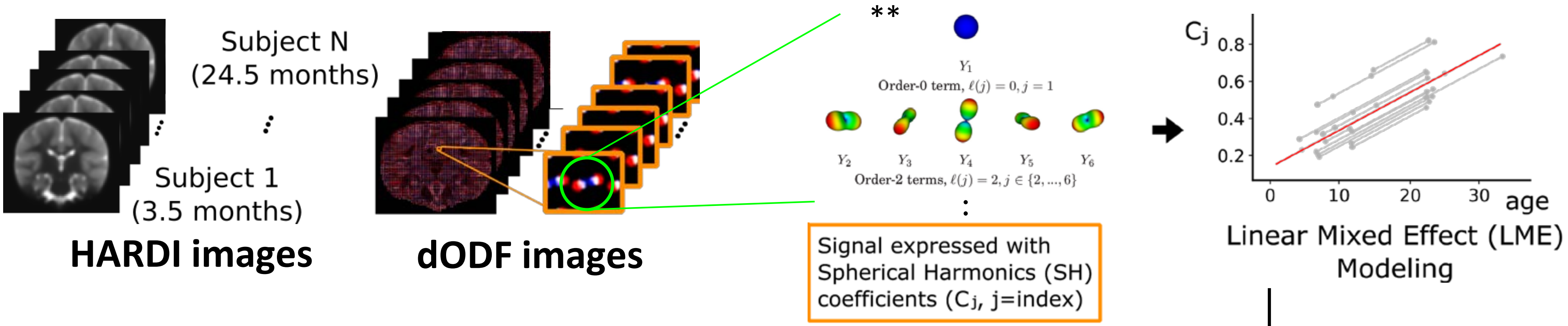


1) Calculating nonlinear deformation of each subject into atlas space.

2) Mapping reoriented diffusion maps into atlas space.

*Yap, et al., IEEE transactions on medical imaging (2012)

Longitudinal dODF atlas construction



- Analytical q-ball based diffusion orientation distribution function (dODF)* calculated for each voxel.†
- LME model for spherical harmonics (SH) coefficients for the population of subjects and repeated measures over time.

$$c_j \sim X\beta + Z\alpha + \epsilon,$$

β = a fixed effects vector → Age

X = [1, t]

α = a random effects coefficient → Subject

Z = a design matrix

ε = errors

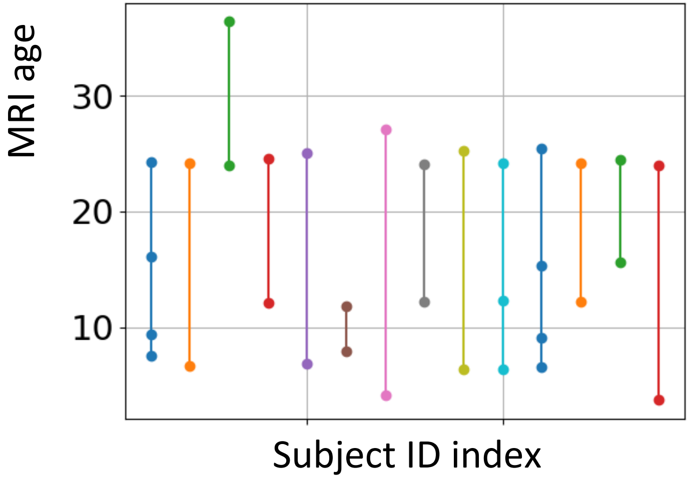
*Descoteaux, Magnetic Resonance in Medicine, 2007

**Descoteaux, High Angular Resolution Diffusion MRI: from Local Estimation to Segmentation and Tractography, 2010

† J Jiang, Linear and generalized linear mixed models and their applications, 2007

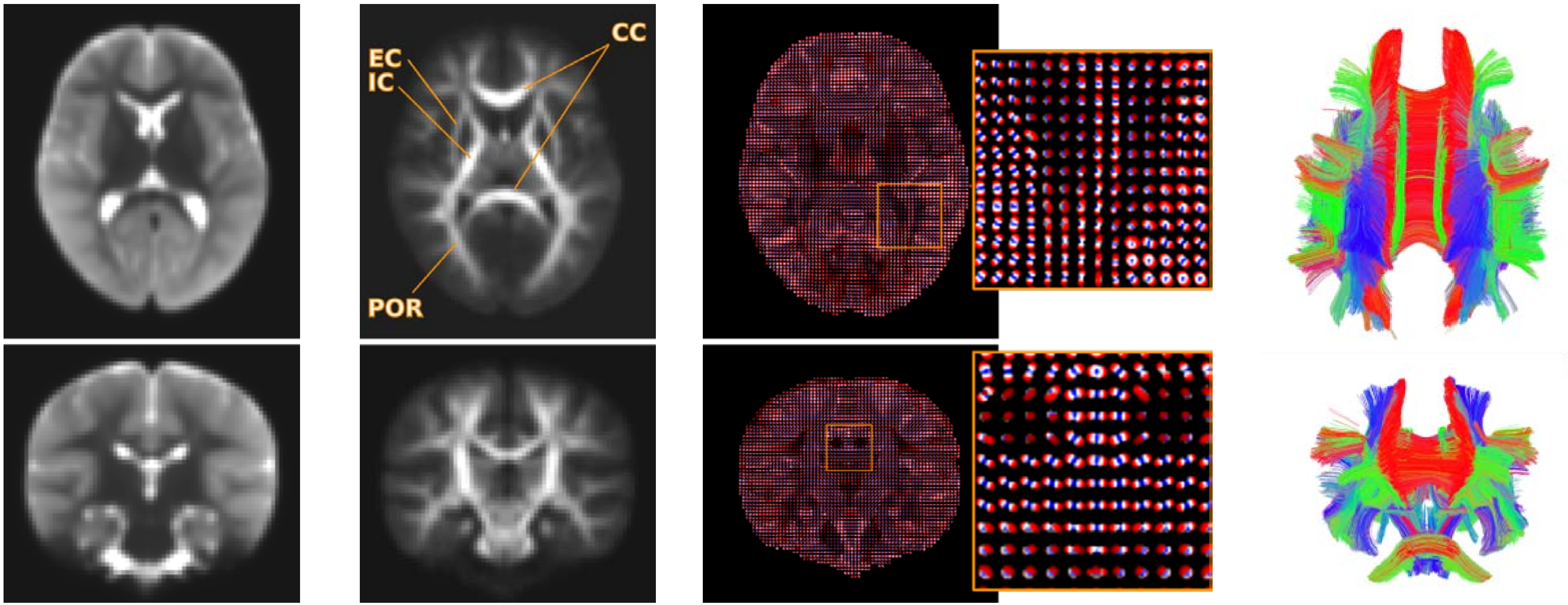
RESULT: ACE-IBIS* Clinical Data

- Autism infant imaging project (ACE-IBIS)
- HARDI 64dir from 3-T Siemens TIM Trio Scanners
- Quality control techniques include DTIPrep** and Q-space resampling†
- Longitudinal study 3- to 36- month
  - 33 images from 14 healthy infants



*Autism Centers of Excellence Infant Brain Imaging Study
**Oguz et al., Front. In Neuroinformatics, 2014
† Elhabian et al., ISBI, 2016

RESULT: Longitudinal DW-MRI Infant Atlas



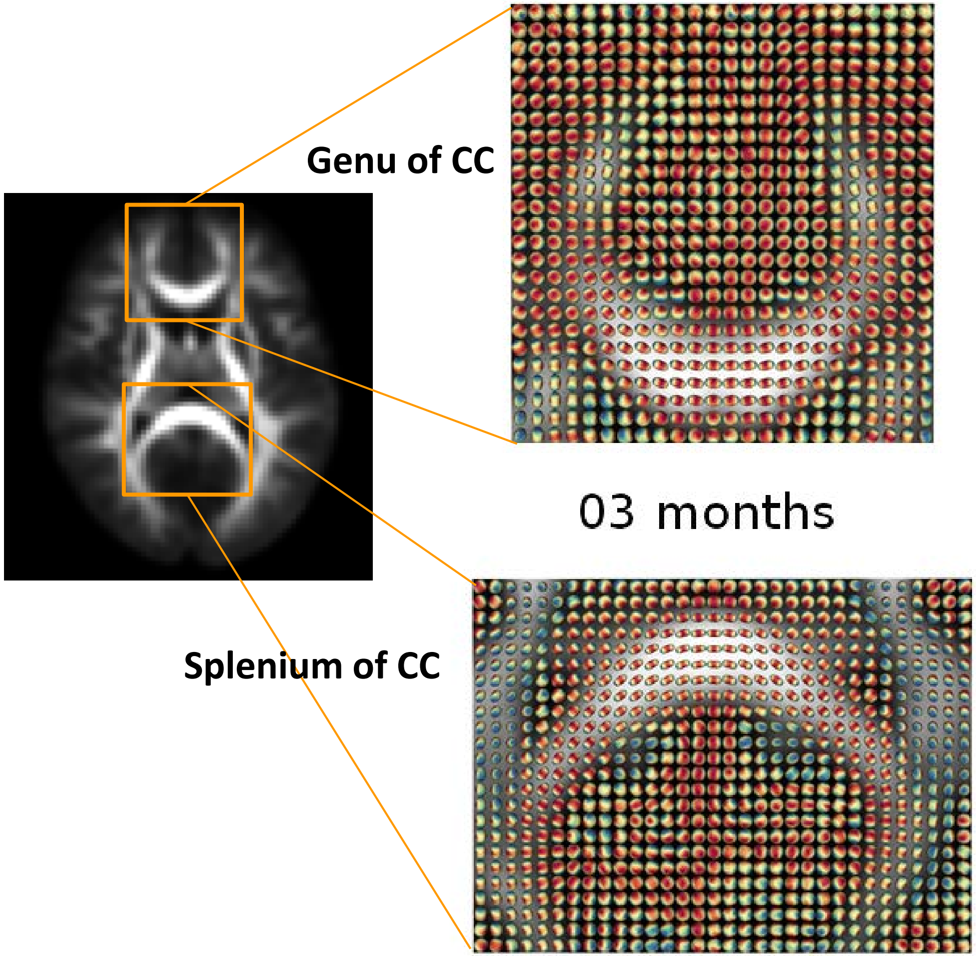
Baseline

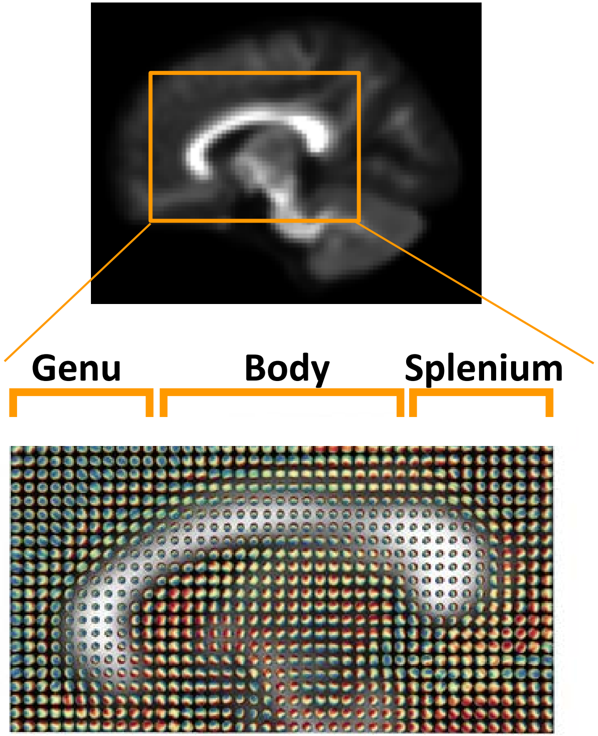
Fractional Anisotropy

Diffusion orientation distribution function (dODF)

Tractography

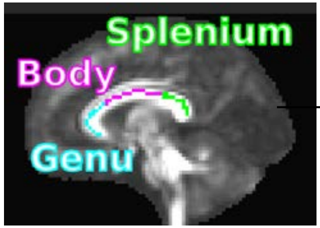
Analysis of corpus callosum





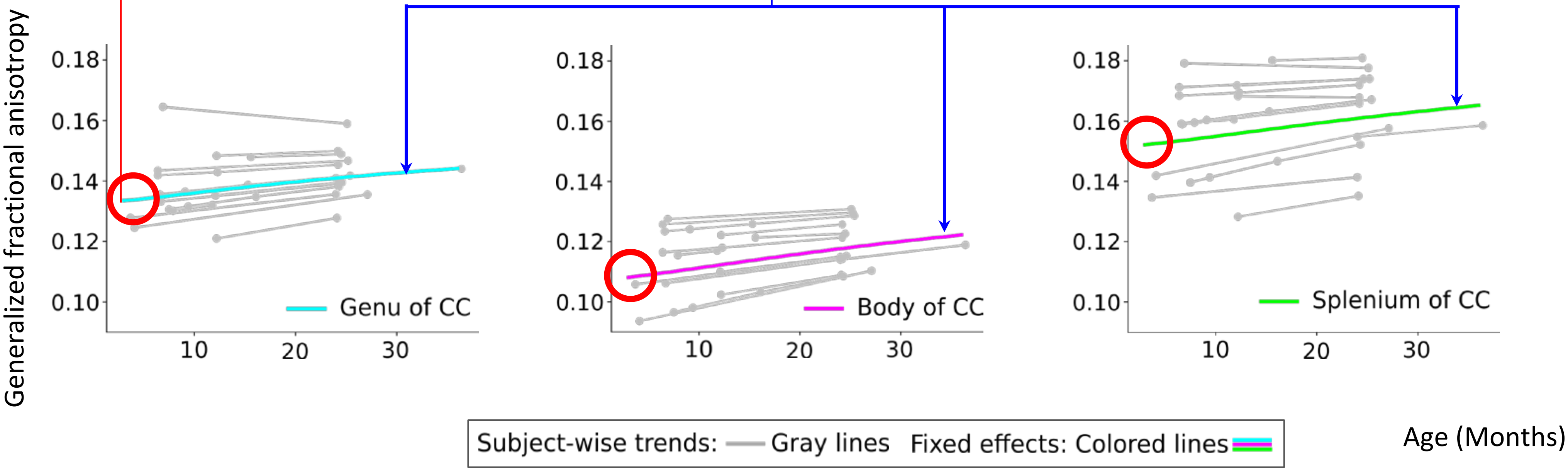
Corpus Callosum (CC)

RESULT: Evaluation based on Longitudinal GFA Changes



- Generalized fractional anisotropy (GFA) calculated for genu, body, and splenium of the corpus callosum

- Splenium of CC starts with **higher GFA***
- **Positive slope** = more anisotropic due to WM development



*Geng, X., et al., Neuroimage, 2012

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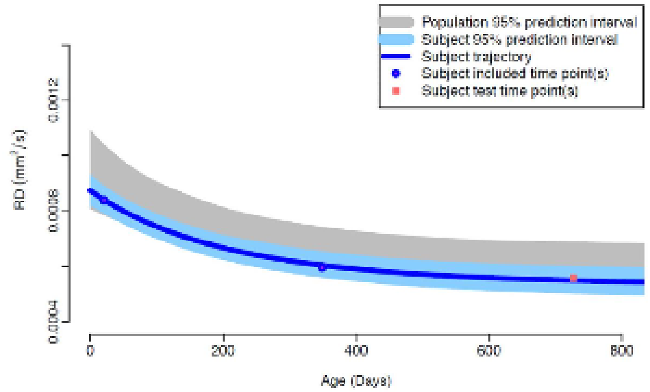
Conclusion & Future Work

- **Done**: Framework to build a continuous longitudinal HARDI brain atlas based on statistics of dODF SH coefficients, applied to longitudinal data of healthy developing infants.
- **Goal**: To represent statistical normative model of dODFs over infant age.
- **Todo**: Explore nonlinear model.
- **Todo**: Modeling of population and subject specific confidence intervals (Sadeghi Neuroimage 2013).

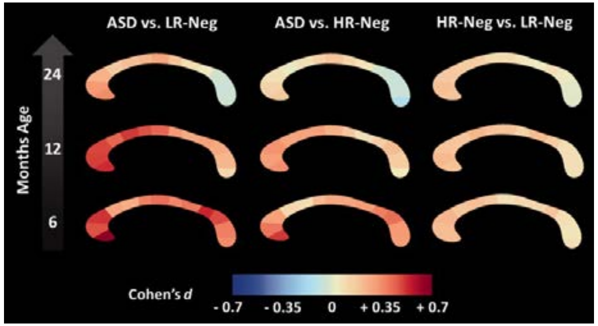


This work was supported by the NIH grants R01-HD055741-12, 1R01HD089390-01A1, 1R01DA038215-01A1 and 1R01HD08812501A1. We are thankful for research discussions with Dr. Ragini Verma.

Hierarchical Multi-Geodesic Model for Longitudinal Analysis of Temporal Trajectories of Anatomical Shape and Covariates

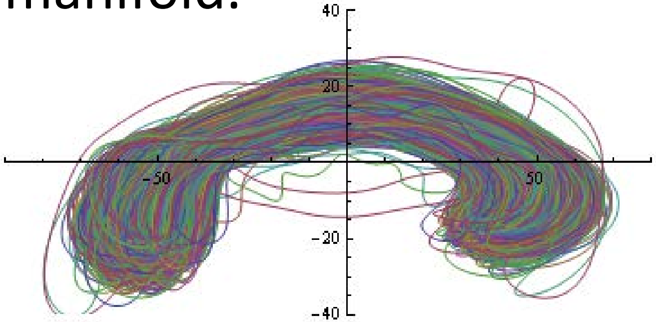
Sungmin Hong, James Fishbaugh, Jason J. Wolff, Jane Paulsen, Martin A. Styner, Guido Gerig

- **Approaches so far:**
  - Statistical shape modeling followed by generalized linear modeling with covariates and group testing (e.g. Wolff et al., Brain 2015).
- **New:**
  - Novel hierarchical multi-geodesic model that can account for the effect of subject-specific covariates to the development (slope) of a shape change.
- Goal:
  - Improved understanding of shape/covariate relationship.

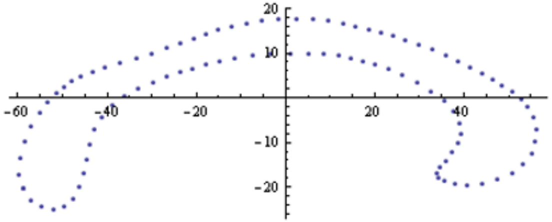


Shape representation and statistics

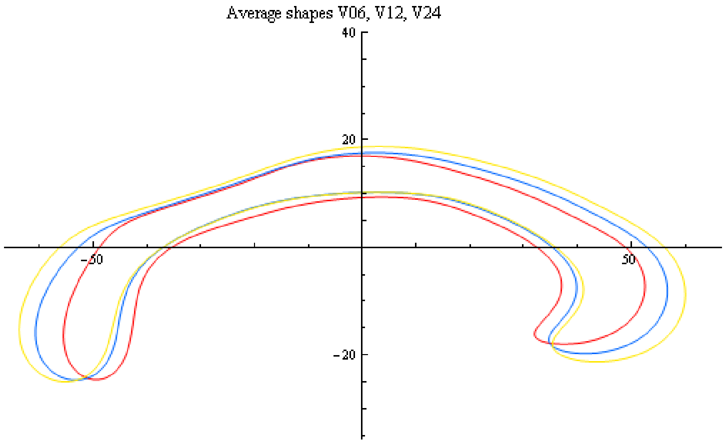
Shape space is non-Euclidean: Geodesic model on Riemannian manifold.



1040 corpus callosum shapes, ACE-IBIS, sampled by boundary points.



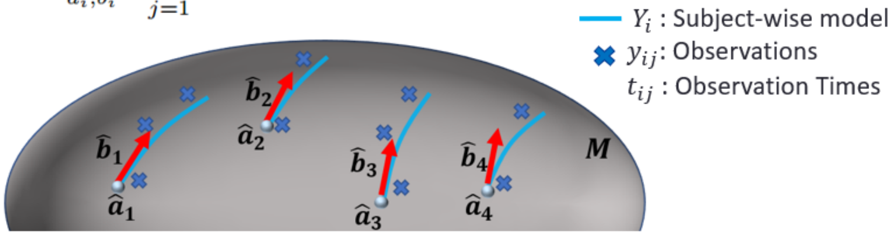
Longitudinal Shape Change per Subject



Hierarchical Model ("mixed effects model", but covariate and time)

Estimate a subject-wise trend as a univariate geodesic model [1].

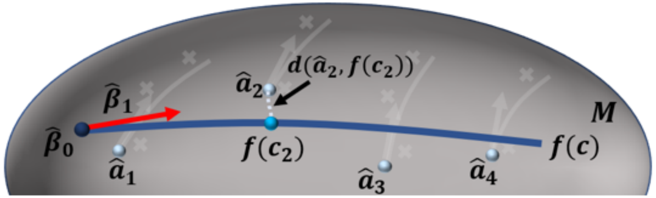
$$(\hat{a}_i, \hat{b}_i) = \underset{a_i, b_i}{\operatorname{argmin}} \sum_{j=1}^{N_{obs}^i} d^2(y_{ij}, Exp(a_i, b_i t_{ij})), \qquad Y_i = Exp(\hat{a}_i, \hat{b}_i t)$$



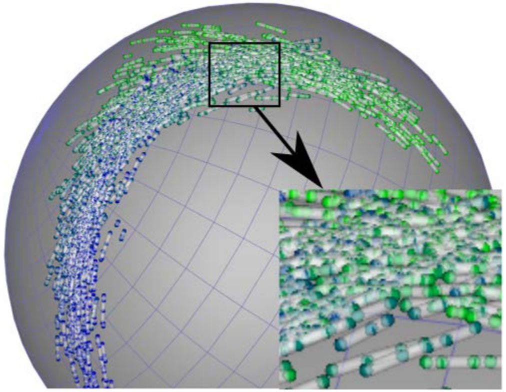
The intercept model $f(\eta)$ formulated as a multivariate geodesic model [2].

Models the effects of covariates to the baselines of subject-specific trends.

$$f(\boldsymbol{\eta}) = Exp(\beta_0, \beta_1\eta_1 + \ldots + \beta_{N_\eta}\eta_{N_\eta})$$

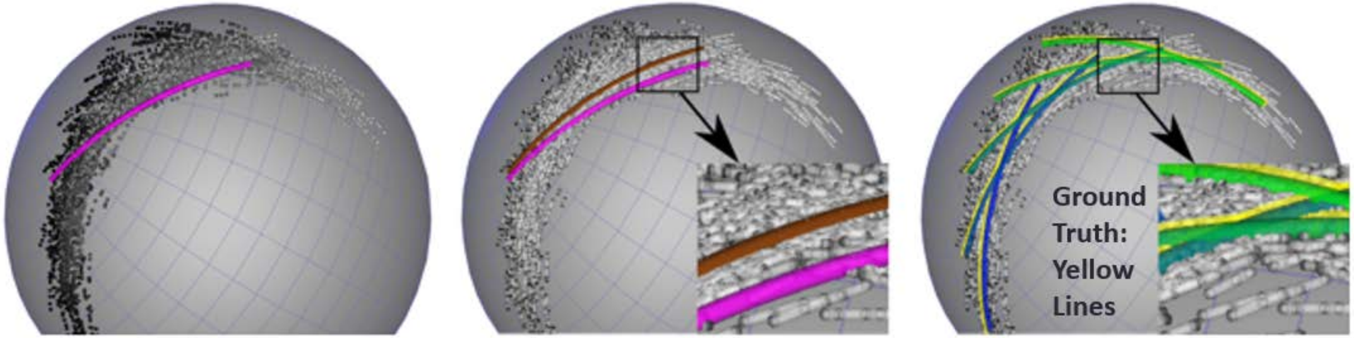


Synthetic Model: Statistical Analysis in Complex Shape Space



1000 subjects with 3500 points total,
covariate c = [0..5]

Lines: longitudinal subject trends



Geodesic Model

Hierarchical Geodesic Model

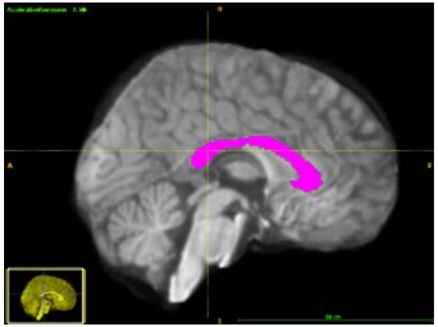
Proposed
Hierarchical Multi-Geodesic Model

Geodesic and Hierarchical Geodesic models fail, cannot account for covariate.

Proposed HMS: Proper model of covariate and individual trends

Study on ACE-IBIS Data (72 shapes, 24 ASD subjects)

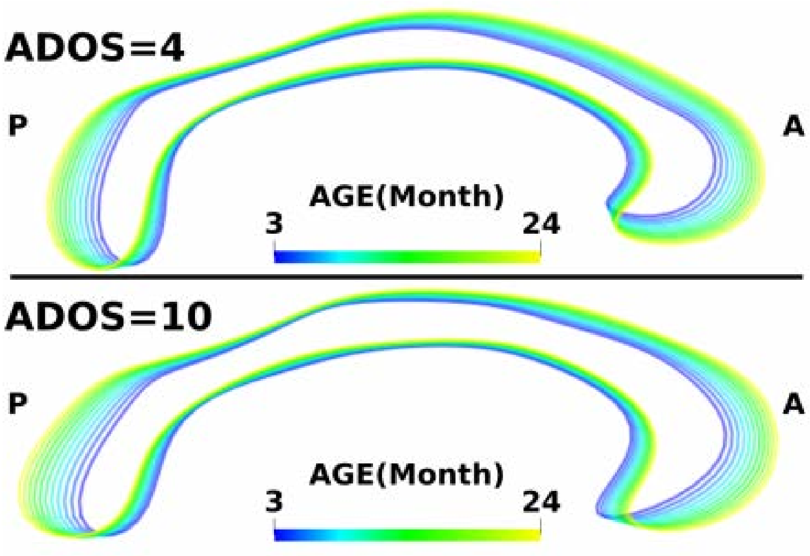
Corpus Callosum



Autism Diagnostic Observation Schedule (ADOS) Score

- Clinical test score on the behavioral and cognitive abilities
- 4 : Low ~ 10 : High

Shape Space : Scale x Kendall Shape - $\mathbf{M} = \mathbf{R} \times \mathbf{CP}^{\mathbf{k-2}}$



Finding: Increased expansion of the anterior CC (genu and rostral body) over time for subjects with higher ADOS scores confirms expansion of CC in ASD.

* **S. Hong**, **J. Fishbaugh**, J. Wolff, M. Styner, **G. Gerig**, "HMG Model for Longitudinal Analysis of Temporal Trajectories of Anatomical Shape and Covariates," MICCAI 2019 (To appear)

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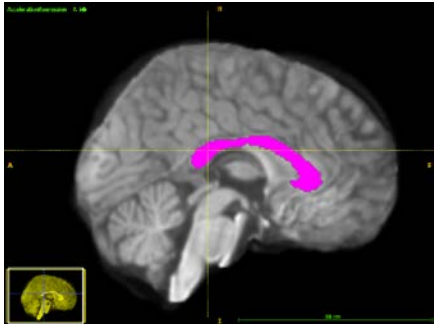

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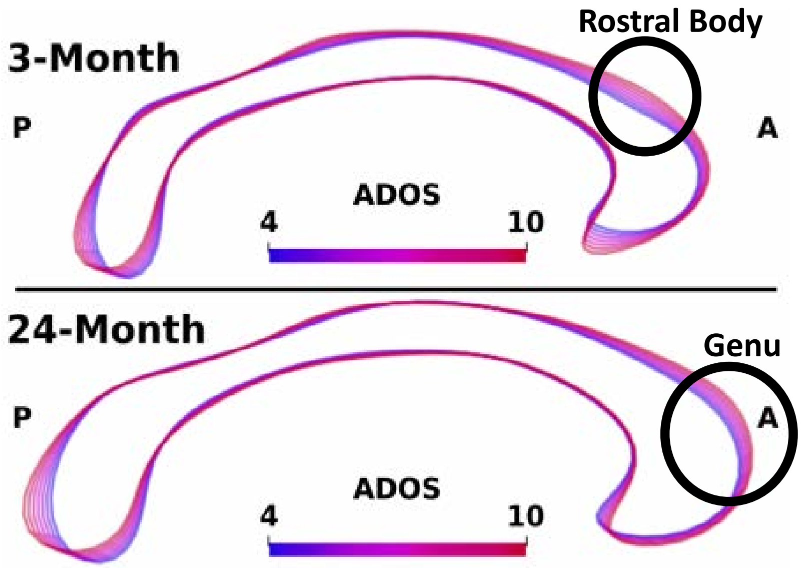

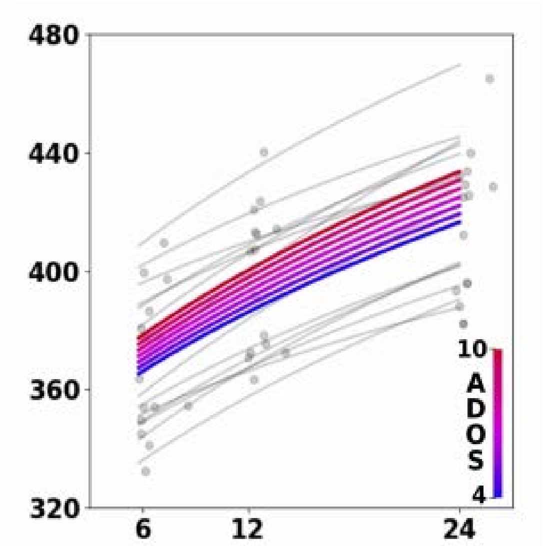

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