Mapping Brain Changes Over Time during Development: Challenges, Limits and Potential

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Outline

- 1. Imaging Technology for Pediatric Imaging
- 2. Analysis of structural MRI
- 3. Analysis of DTI
- 4. Multimodal MRI/DWI Analysis
- 5. Towards Longitudinal Analysis





I: MR Imaging of Children

- Non-sedated neonates and children
 - Subject cooperation difficult
 - Motion problems
 - Safety issues
- Solutions:
 - MTRAs with special training
 - High-speed high-field imaging, high spatial resolution
 - Parallel Acquisition
 - Mock Scanner (Training)
 - Motion correction



Courtesy LeBihan 2005





High-Speed Imaging: Neonatal MRI at 3T





 T1 3D MPRage
 FSE T2w
 FSE PDw

 or FLASH
 1.25x1.25x1.95mm3
 1.25x1.25x1.95 mm3

 1x0.9x0.9 mm3
 1x0.9x0.9 mm3
 1x0.9x0.9 mm3



UNC Weili Lin: 3T Siemens Allegra Scan Time: Structural MRI (T1 & SpinEcho): 8min, DTI: 4min -> 12 Min tot





Prenatal MRI / Premies





Julia Fielding, UNC (intra-utero)

Petra Hueppi, Geneva and Harvard (26 weeks premie)





Training of infants: Mock Scanner



- Old MRI scanner used for practice sessions (pictures Yale Univ.)
- Subjects learn to remain still for up to 30 minutes
- Head tracking coupled with video presentation (Duke)



High-Speed Imaging: Infant MRI at 3T



UNC Weili Lin: 3T Siemens Allegra





Example: UNC Scan Success Rate

Siemens 3T Allegra, Weili Lin & team

CONTE SZ Study, started 2002

Singletons	Neonates	Follow-up 1yr	Follow-up 2yrs
Controls	156	42	34
SZ & BP	33	15	9
MVM	34	12	2
Total	223	69	45
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Attempted	251	110	77
Success Rate	89%	63%	58%

Twin Study started 2006

Twin Pairs	Neonates	Follow-up 1yr	Follow-up 2yrs
Controls MZ/DZ	67	28.5	12.5
Attempted	69	34	18
Success Rate	97%	84%	69%





New Technology: MRI Motion Correction

GE: PROPELLER* - Motion Correction Imaging (unique pattern of k-space filling that acquires data in radial "blades" rotating in sequence) Siemens: Navigator pulse for online correction (Flash T1, courtesy of MGH).





Fig C 14 Slice through average of 3 FLASH scans without motion correction (left) and 3 FLASH scans with motion correction (right).





Most Recent: Parallel Acquisition and matrix coils



23 channel array for 1.5T

SNR Maps Grad. Echo

Normalized to volume coil average (=1.0)

SNR gain: 4 fold in cortex 1.75x in corpus callosum







Volume coil



23 channel array



23 Channel "Bucky"





Courtesy Bruce Rosen, MGH

coil

UNC – MGH Project: Modeling Head Shapes for Infant Coil Design



Statistical modeling of head shapes for infant matrix coils: Collaboration with Larry Wald, MGH and W. Lin, UNC





Example: 95% head and brain size for 2yr group.







Profile PD normalized images \rightarrow Coil Sensitivity Profiles

images



T2

PD

Parallel coil





T1



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T1 Parallel coil

T1 Volume coil







Images used for Measurements: Calibration









Example Duke: BIAC BIRN scanner calibration



2. Structural MRI

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Contrast changes in early development



5D



5D



6Mo



6Mo



14Mo



Early myelination







Courtesy Keith Smith, UNC Radiology

Contrast changes in early development



UNC/Utah infant neuroimaging study



Neonatal MRI Segmentation



Marcel Prastawa, John H. Gilmore, Weili Lin, Guido Gerig, Automatic Segmentation of MR Images of the Developing Newborn Brain, (MedIA). Vol 9, October 2005, pages 457-466









4 and 6 month old subjects



Intermediate stage of contrast flip between white and gray, with no differentiation in T1w at 4-6 mt and in T2 at 6-8 mt.

T1 and T2 are not in sync w.r.t. tissue contrast





Challenge in Segmentation of 1 years olds



T1w axial and zoomed

T2w axial and zoomed

Difficulties for tissue segmentation:

- Strong bias inhomogeneity
- Gradual degree of myelination decreasing from central to peripheral regions
- Very low contrast in cortical white/gray
- T2 lags behind T1 in its ability to depict wm contrast and therefore even shows less





Follow-up: Hi-res T1 (Weili Lin, UNC)



T1 MRI of same child at 1yr and 2yrs with wm probability maps: wm/gm boundary more fuzzy at 1yr.







Brain Segmentation 1year old



- Advanced version of expectationmaximization segmentation (M. Prastawa)
- Prior: Age-specific atlas
- Nonlinear registration of atlas to subject
- Robust, nonparametic clustering
- Parametric bias field

CORRECTION THE BRAIN INSTITUTE THE UNIVERSITY OF UTAH



Current Solution: Individual Tissue Segmentation at each time point



Cortical Thickness Analysis



Cortical thickness in mm

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3. DTI in Infants



Population-based analysis of fiber tracts

Example: 150 neonate DTI mapped to unbiased atlas



Casey Goodlett, Sarang Joshi, Sylvain Gouttard, Guido Gerig, SCI Utah (MICCAI'06, MICCAI'08, NeuroImage (in press)





Concept: Group statistics of fiber tracts



Atlas Building



Challenges:

- Linear vs. nonlinear registration (Gee et al., Joshi et al., Goodlett et al., ..)
- Reorientation of tensors (Alexander, Jones)
- Interpolation of DWI or tensors (Fletcher, Arsigny, Westin&Kindlman)





Co-registration of image sets





Not registered

Linear registration (affine)





Co-registration: From linear to nonlinear





Linear registration (affine)

Nonlinear registration (fluid)





Application: Neurodevelopmental Statistical Atlases



Neonate (N=95)



1 year (N=25)





Collaborative research on studying the early developing brain with John H. Gilmore and Weili Lin, UNC Chapel Hill





2 year (N=25)

Adult (N=24)





Neurodevelopmental atlas









Sample Quantitative Statistics









Sample Quantitative Statistics









Fiber Tractography via Atlases



Neonate atlas DTI











Tract Parametrization and Analysis



Corouge et al. *Fiber tract-oriented statistics for quantitative diffusion tensor MRI analysis*. Medical Image Analysis 2006. FiberViewer software - http://www.ia.unc.edu/dev/





Pediatric Example: Genu Tract 1-2yrs











Pediatric Example – Left motor tract







Statistical analysis of tracts as 1-D curves: Functional data analysis (FDA)



"Group Statistics of DTI Fiber Bundles Using Spatial Functions of Tensor Measures" Casey Goodlett, P. Thomas Fletcher, John Gilmore, and Guido Gerig, MICCAI 2008, NeuroImage (in press)

Hypothesis testing and discriminant analysis on first k PCA modes (Hotelling T^2) → Type and Location

of group differences.





DTI is part of multi-modal MRI protocol



T1 MPRage. T2 3D TSE, MD, FA (2yrs old. Weili Lin, UNC)





Quantitative Tractography to study early wm development



John H. Gilmore et al., Early Postnatal Development of Corpus Callosum and Corticospinal White Matter Assessed with Quantitative Tractography, AJNR Nov. 2007



- FA does not explain degree of myelination and structuring
- Combined use of DTI, T1w and T2w





5. Towards Longitudinal Analysis

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Fallacy of global versus local analysis: Nonlinear growth of human brain

Brain development during childhood and adolescence: a longitudinal MRI study

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Longitudinal Study Design: Normative NIH Brain Study



Challenges:

- Mixed Crosssectional and longitudinal design
- Missing data (1, 2 or 3 data points per subject)



Longitudinal changes of MR images of population



Properties of data

- Correlation, similarity between repeated MR scans
- Missing Data
- Unbalanced spacing, different time points
- Correlation between tissues, inter-subject variance, etc.
- Multivariate features: Dimensionality
- Regression not suitable





Challenge: Multivariate Longitudinal data analysis



Figure 2. Scatter plot of our WM, GM. CSF data versus time. An illustration of irregular data that has uneven sampling at time axis for different subjects. CSF: red dot, GM: green box, WM: blue triangle.



Figure 4. 95 % confidence interval of the growth curves of three brain tissues. CSF: red dash line, GM: green dot-dash line, and WM: blue solid line.



Figure 7. Derivatives of the parametric growth curves of three brain tissues. CSF: red dash line, GM: green dot-dash line, and WM: blue solid line.

Multivariate Longitudinal Statistics for Neonatal-Pediatric Brain Tissue Development, Sh. Xu, M. Styner, J.H. Gilmore, G. Gerig, SPIE 2008

Multivariate Nonlinear Mixed Model to Analyze Longitudinal Image Data: MRI Study of Early Brain Development, Shu Xu et al., MMBIA 2008





Challenge: Multivariate Longitudinal data analysis



Figure 2. Illustration of individual growth trends. A spaghetti plot that connects repeated measurements of the same individual is shown. The two red upper and lower bound curves are generated by varying β_1 and β_3 only and with fixed β_2 , which indicates population variance can be captured by varying only β_1 and β_3 .



Figure 3. Illustration of individual growth trends. A spaghetti plot that connects repeated measurements of the same individual is shown. Multiple features that describe the three dimensional head size derived from each MRI brain image of neonates and young children is illustrated. X dimension: red dots connected by dashed times; Y dimension: blue triangles connected by dotted times; Z dimension: green stars connected by solid lines.



Figure 4. Population growth trajectories of head size dimension X, Y, Z plotted against the original data points ranged from age 0 to around 6 years old. A third population of 22 infants aged from 4 to 8 months old (in black dashed circle) are also plotted to validate the soundness of the average growth estimation. Symbols are the same as those in Fig. 3.



Figure 5. Growth rates of head size dimension X, Y, Z between birth to around 6 years old. X dimension: dashed red lines; Y dimension: dotted blue lines; Z dimension: solid green lines.

Multivariate Longitudinal Statistics for Neonatal-Pediatric Brain Tissue Development, Sh. Xu, M. Styner, J.H. Gilmore, G. Gerig, SPIE 2008

Multivariate Nonlinear Mixed Model to Analyze Longitudinal Image Data: MRI Study of Early Brain Development, Shu Xu et al., MMBIA 2008





Summary

Key topics related to imaging of early development:

- Imaging itself is great challenge
- Continuous contrast, size, shape changes:
 - Challenge for image registration
 - Challenge for image segmentation (thin cortex, very low contrast of subcortical structures)
 - Contrast flip wm/gm in anatomical images
- Myelination: Appearance changes within tissue: Should not affect registration!
- Longitudinal studies: Requires study of temporal changes rather then cross-sectional differences





Conclusions

- Pediatric Imaging & Image Analysis:
 - Amazing progress of imaging technology
 - Image processing tools newly developed
 - Wealth of new results
 - Fascinating research area: Full of discoveries
 - Potential impact: Better understanding \rightarrow early detection \rightarrow therapy
- Research field needs:
 - Multidisciplinary research: Biology, anatomy, medicine, CS, statistics
 - Link between MRI findings and <u>underlying neurobiology</u>
 - Sharing of data and analysis tools
- Fundamental computational and statistical problems:
 - Everything changes: Contrast, size, shape, appearance
 - Statistics of growth of images and structures: 4D statistical atlases
 - (Longitudinal) multivariate statistics of imaging features & patient parameters





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Developmental Trajectory: Krabbe's

Behavioral Phenotypes



Description of behavioral phenotypes are instrumental in understanding the disease's process and its impact in neurological function. **Gross Motor**



Notion of <u>normative model/atlas</u>: Describe patients relative to population statistics of healthy development.



