The ANTs Longitudinal Cortical Thickness Pipeline

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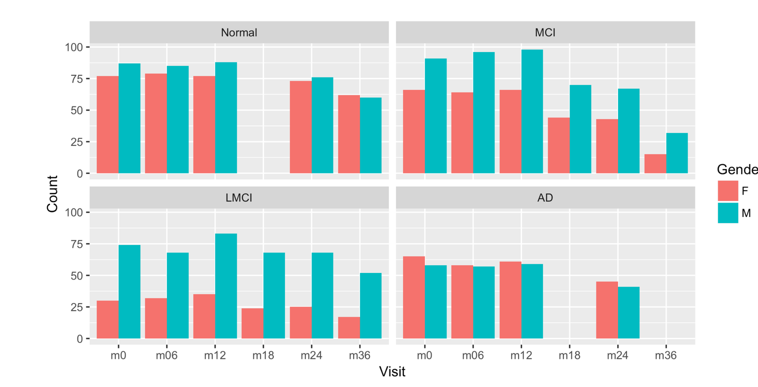
BACKGROUND

- Longitudinal studies of development or disease in the human brain have motivated the acquisition of large neuroimaging data sets and the concomitant development of robust methodological and statistical tools for quantifying neurostructural changes.
- Longitudinal-specific strategies for acquisition and processing have potentially significant benefits including more consistent estimates of intra-subject parameters while retaining predictive power.
- Much research has been devoted to exploring methodologies for properly exploiting longitudinal studies and avoiding various forms of processing bias.[1]
- Previously[2] we introduced the Advanced Normalization Tools (ANTs) cortical thickness framework which leverages various pre-processing, registration, segmentation, and other image analysis tools that members of the ANTs and Insight Toolkit (ITK) open-source communities have developed over the years and disseminated publicly.
- We introduce the longitudinal version of the ANTs cortical thickness pipeline and demonstrate its utility on the publicly available ADNI-1 data set. In addition, we demonstrate that certain longitudinal processing choices have significant impact on measurement quality in terms of within-subject and between-subject variances.

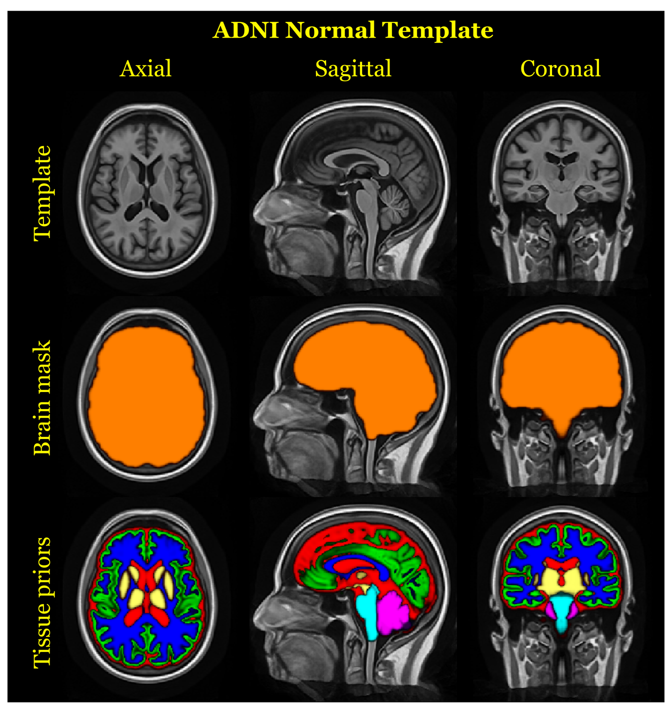
METHODS & MATERIALS

ADNI-1 imaging data

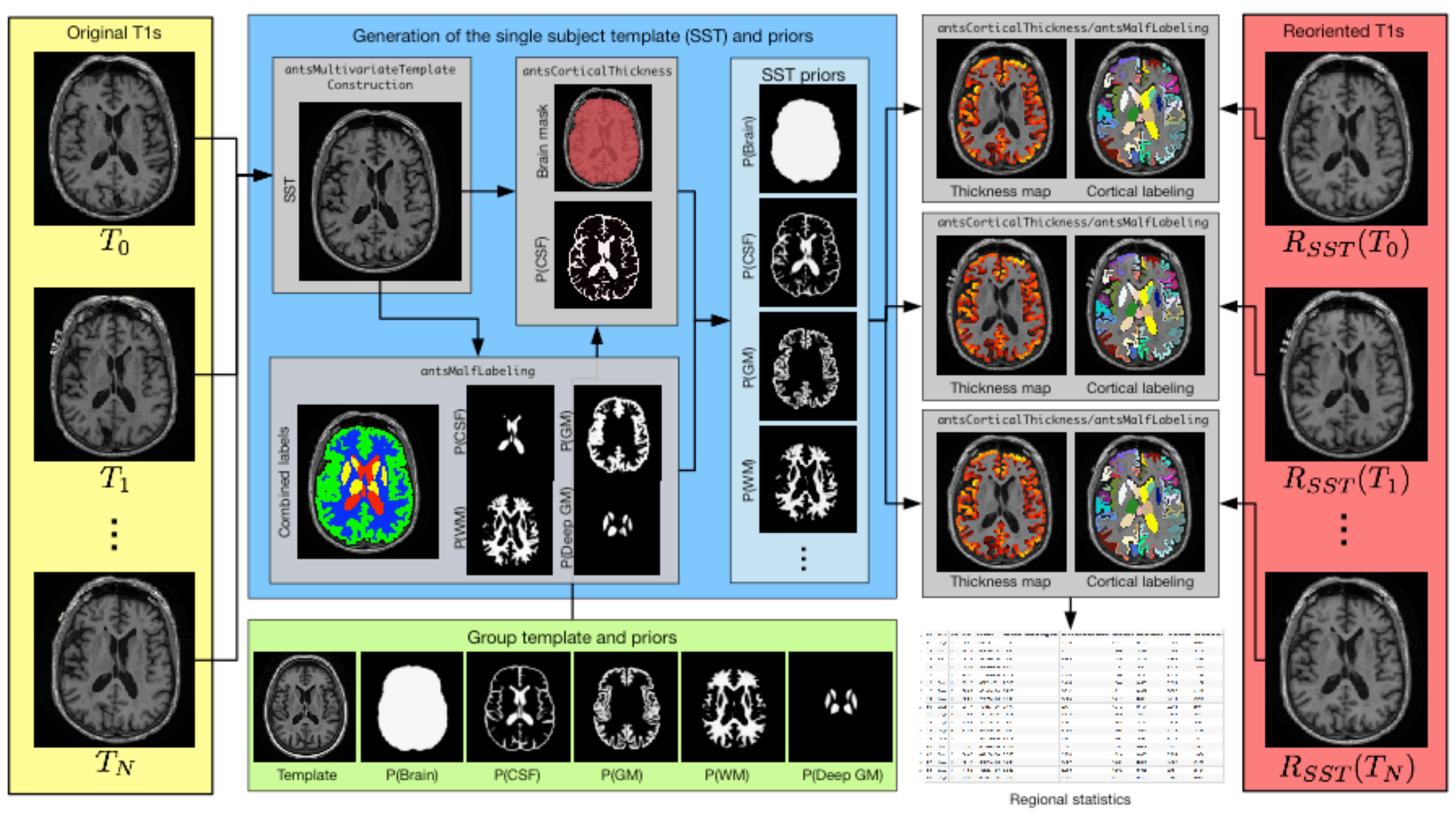


681 total subjects:
- 186 cognitive normals
- 178 MCI
- 128 LMCI
- 123 AD

ADNI ANTs template and priors



ANTs longitudinal pipeline



1. (Offline): Group template and prior probability image creation.
2. Unbiased single-subject template (SST) creation.
3. Application of the ANTs cross sectional pipeline to the SST. This processes the SST based on the group template.
4. Creation of the SST prior probability maps.
5. (Optional): Transform each individual time point to the SST.
6. Application of the ANTs cross-sectional pipeline – with SST as reference template – to each individual time-point image.
7. Joint label fusion to determine the cortical ROIs for analysis.

RESULTS

Evaluation strategy

For the following cortical thickness pipelines:

- FreeSurfer cross-sectional (FS Cross)
- FreeSurfer longitudinal (FS Long)
- ANTs cross-sectional (ANTs Cross)
- ANTs processed in SST space (ANTs SST)
- ANTs processed in native space (ANTs Native)

using the Bayesian LME model

$$Y_{ij}^k \sim N(\alpha_i^k + \beta^k t, \sigma_k^2)$$
$$\alpha_i^k \sim N(\alpha_0^k, \tau_k^2) \quad \alpha_0^k, \beta^k \sim N(0, 10)$$
$$\sigma_k, \tau_k \sim \text{Cauchy}^+(0, 5)$$

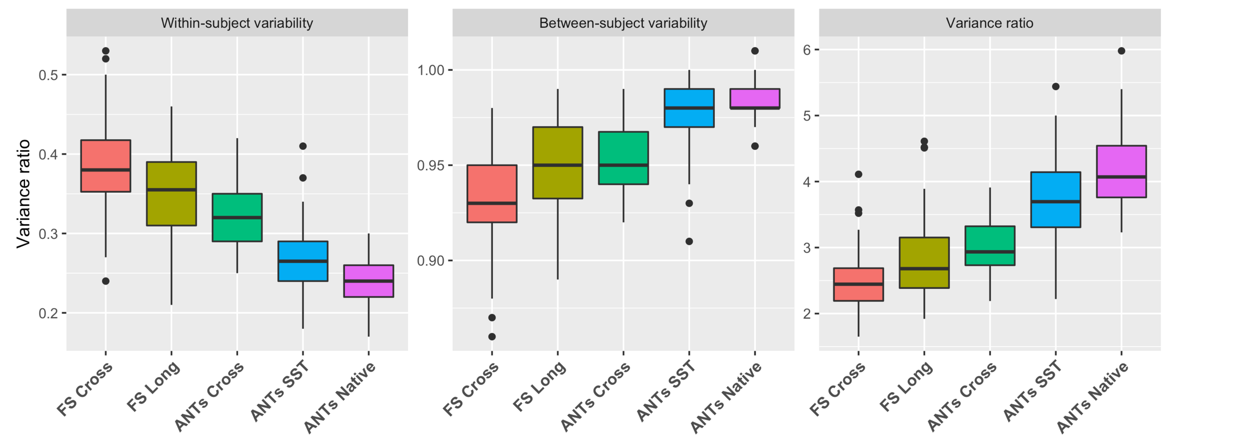
we compute the within-, σ_k, and between-subject, τ_k, variances for each of the 62 Desikan-Killiany-Tourville[3] cortical regions:

1) caudal anterior cingulate (cACC)
2) caudal middle frontal (cMFG)
3) cuneus (CUN)
4) entorhinal (ENT)
5) fusiform (FUS)
6) inferior parietal (IPL)
7) inferior temporal (ITG)
8) isthmus cingulate (iCC)
9) lateral occipital (LOG)
10) lateral orbitofrontal (LOF)
11) lingual (LING)
12) medial orbitofrontal (MOF)
13) middle temporal (MTG)
14) parahippocampal (PARH)
15) paracentral (paraC)
16) pars opercularis (pOPER)
17) pars orbitalis (pORB)
18) pars triangularis (pTRI)
19) pericalcarine (periCAL)
20) postcentral (postC)
21) posterior cingulate (PCC)
22) precentral (preC)
23) precuneus (PCUN)
24) rosterior anterior cingulate (rACC)
25) rostral middle frontal (rMFG)
26) superior frontal (SFG)
27) superior parietal (SPL)
28) superior temporal (STG)
29) supramarginal (SMAR)
30) transverse temporal (TT)
31) insula (INS)

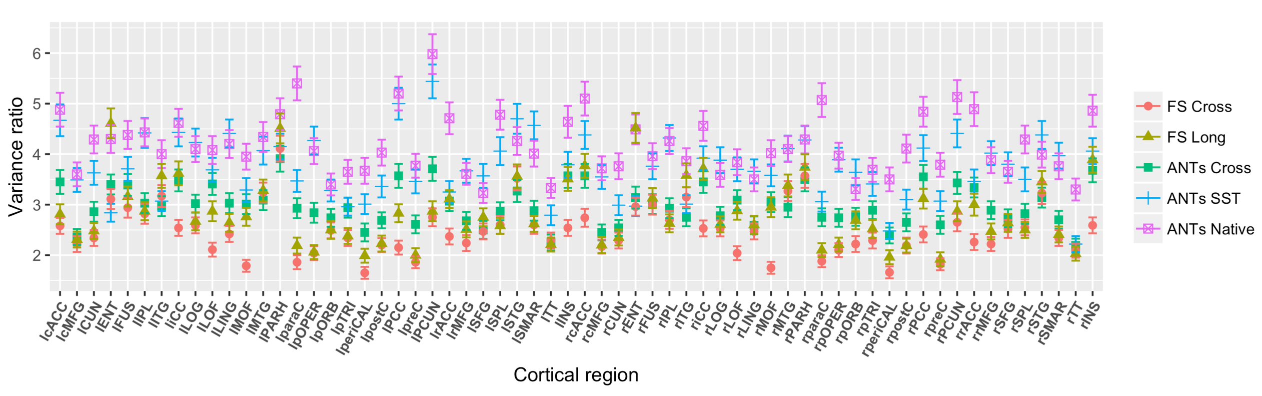
We then calculate the following variance ratio as a comparative performance metric:

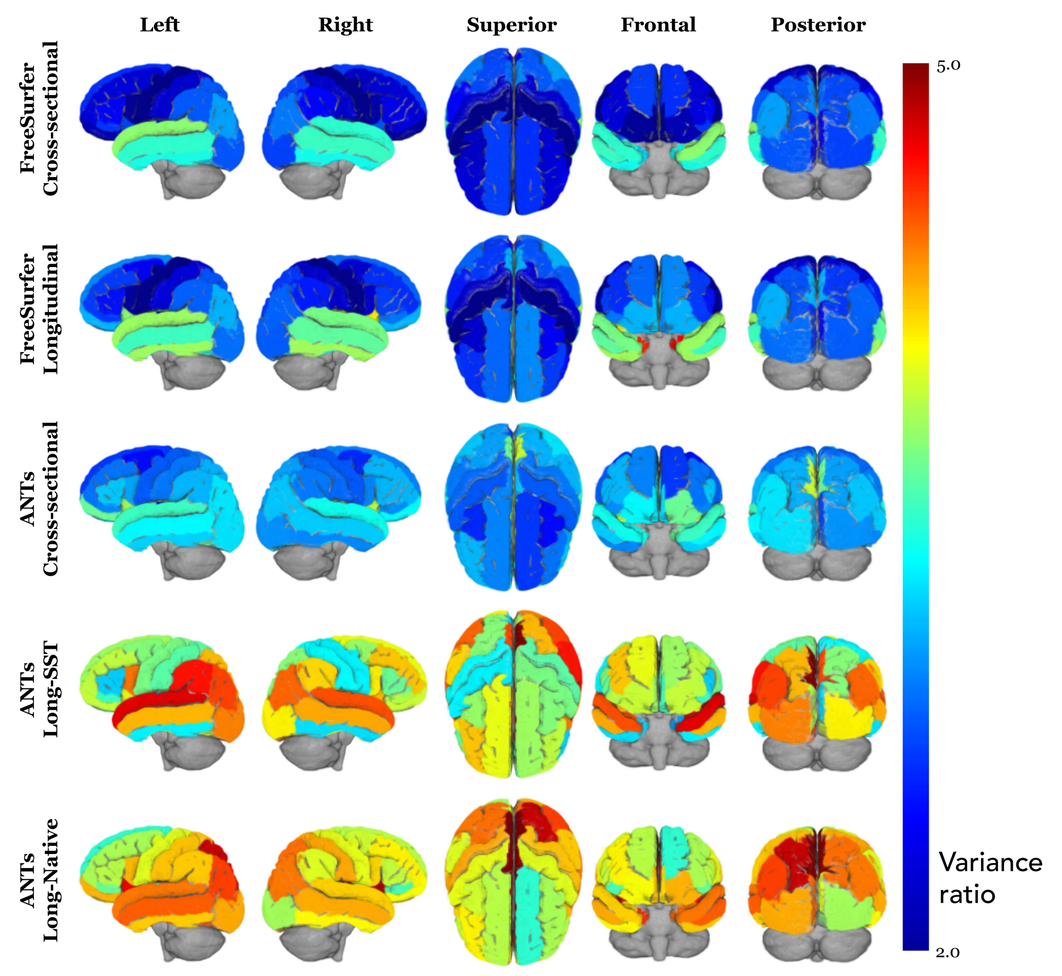
$$r^k = \frac{\tau_k}{\sigma_k}, \quad k = 1, \ldots, 62$$

Global variability comparison



Regional variability comparison





DISCUSSION

Conclusions

- Comparative assessment utilized LME models to determine the between-subject to within-subject variance ratios where higher values indicate greater discriminative capacity.
- In the majority of regions ANTs pipelines outperformed their FreeSurfer counterparts with longitudinal processing in the native space (ANTs Native) performing the best.
- ANTs SST outperformed ANTs Cross over the majority of regions. Regional disparities point to increases in both between-subject and within-subject variances which might be an additional interpolation artifact.

Future direction

- FS Long slightly outperformed all pipelines in the left and right entorhinal regions. This motivates the development of an ANTs-based entorhinal specific pipeline.

REFERENCES

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2. Tustison et al. (2014). Large-scale evaluation of ANTs and FreeSurfer cortical thickness measurements. *NeuroImage*.
3. Klein and Tourville (2012). 101 labeled brain images and a consistent human cortical labeling protocol. *Frontiers in Neuroscience*.

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