Vertex Correspondence in Cortical Surface Reconstruction

Presented by William Ashbee at Trends Center

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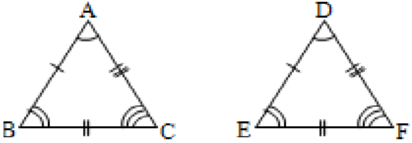
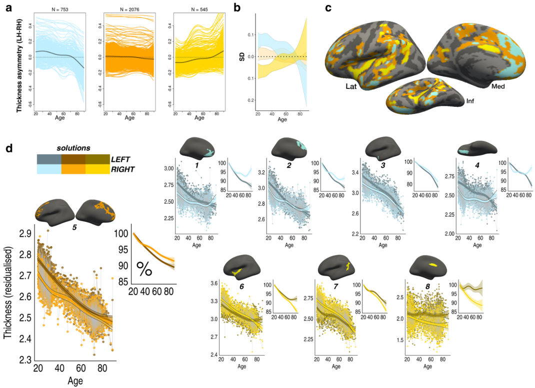
Introduction

- Vertex correspondence determines which vertices in two meshes are mapped onto each other.
- Cortical Surface Reconstruction methods produce meshes, which can be mapped onto a group template.
- Mapping from predicted mesh to group templates allows for group studies.
- Knowing correspondence between prediction and ground truth enables the use of L1 and MSE, instead of Chamfer Distance as a loss.



- $A \leftrightarrow D$
- $B \leftrightarrow E$
- $C \leftrightarrow F$

Motivation: Importance of Group Studies in Alzheimer's Disease Research

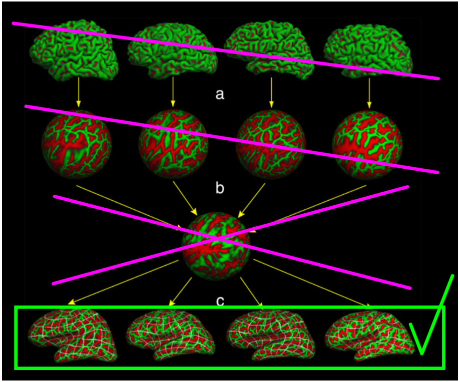


- Regions with leftward asymmetry in early adulthood lose asymmetry with age (blue lines), and regions with rightward asymmetry lose asymmetry over time (yellow lines). [1]

[1] Asymmetric Thinning of the Cerebral Cortex Across the Adult Lifespan is Accelerated in Alzheimer's Disease

Summary of Contributions

- Key Innovations: L1 loss for vertex correspondence, registration and remeshing to fsaverage, and training for group studies on fsaverage allow direct surface prediction in group coordinates.
- Advantages: Skips scanner coordinates and spherical registration while generating surfaces in the group template space.



Introduction - Traditional Methods / contribution

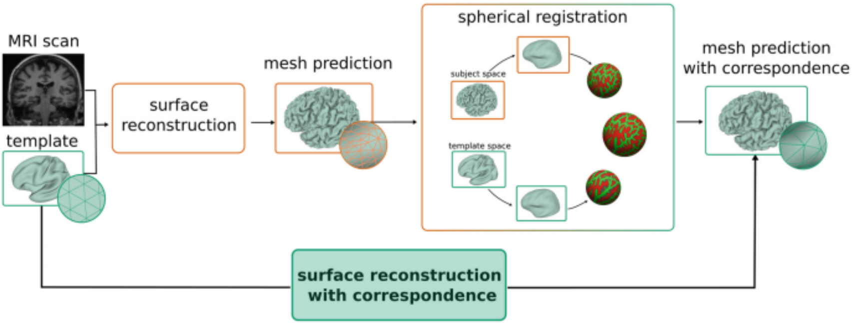
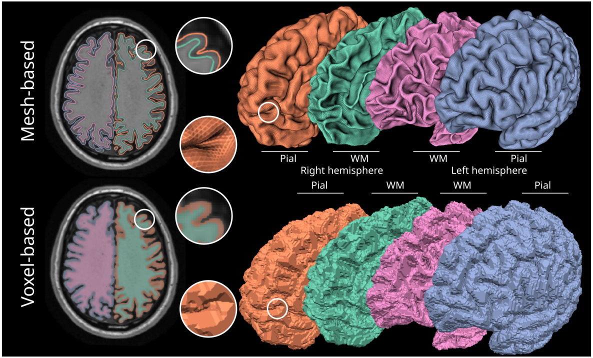


Fig. 1. Top: Overview of existing cortical surface reconstruction approaches, that are dependent on a cumbersome spherical registration as post-processing to obtain vertex correspondence to a template. Bottom: Our approach directly yields surface predictions with correspondence to the input template and does not require any registration.

- V2CC essentially skip spherical registration as a post processing step by training on the end results in group coordinates.

Background - Cortical Surface Reconstruction

- Extracting pial and white matter surfaces from MRI.
- Important for computing metrics like cortical thickness, curvature, and gyrification.

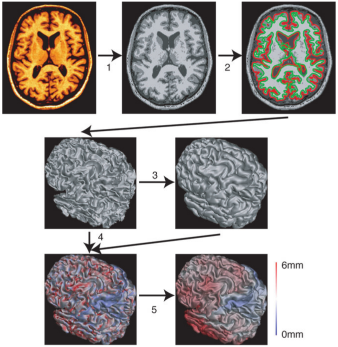


[a]

[a] Image from Neural deformation fields for template-based reconstruction of cortical surfaces from MRI

Background of traditional Cortical Thickness calculations

- First, the images are non-uniformity corrected and registered into stereotaxic space (e.g. MNI 152).
- The sMRI are then segmented
- Fit with a white matter surface.
- The gray surface is found by expanding out from the white.
- Cortical thickness is measured at every vertex

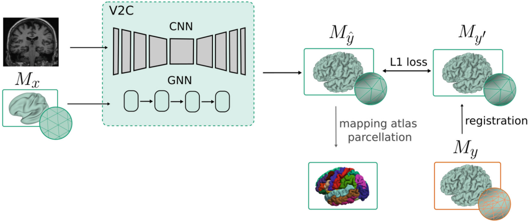


[a]

[a] Image from Focal Decline of Cortical Thickness in Alzheimer's Disease Identified by Computational Neuroanatomy

Method Overview

- Pre-processing with registration.
  - MRI is registered to MNI 152 coordinates.
  - ground truth surfaces are registered to `fsaverage` template using [2]`mri_surf2surf`
- L1 loss for vertex correspondence.
- Network Backbone: V2C, adaptable to other methods.

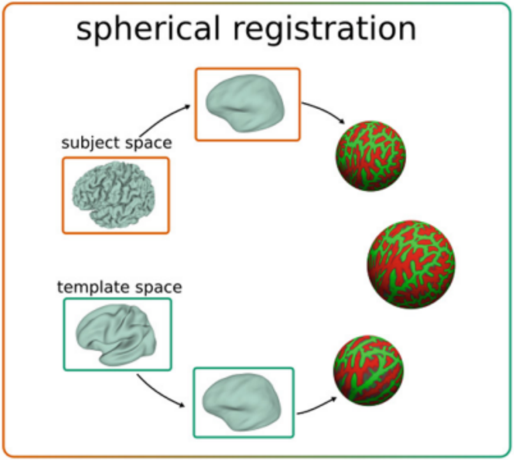


2

[2]`mri_surf2surf --s $sub --hemi $hemi --sval-xyz $surf --trgsubject fsaverage --tval $SAVE_DIR/$sub/surf/$hemi.$surf --tval-xyz $SAVE_DIR/$sub/mri/orig.mgz` via email from author A. Rickmann

Method - fsaverage registration

- All ground truth surfaces are spherically registered and remeshed to fsaverage template, which is *FreeSurfer*'s coordinate system for surface group studies.



Relevant Coordinate Systems in V2CC and FreeSurfer

MNI Coordinates – V2CC MRI

- Used for volumetric data normalization
- Common reference space for voxel-based analyses
- Useful for aligning individual brains to a standard template

Talairach Coordinates – internal FreeSurfer

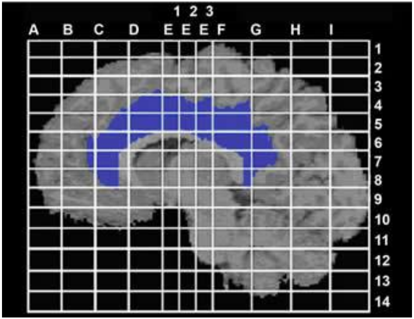
- Provides anatomical localization
- Used for standard anatomical reference in brain mapping
- Helps in comparing results across different studies and software

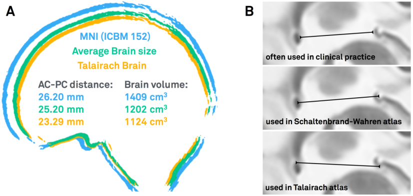
fsaverage Coordinates – V2CC surface ground truth

- Surface-based standard space for cortical surface analysis
- Essential for inter-subject surface alignment
- Used for mapping individual cortical surfaces to an average template
- Facilitates group analysis and comparisons on a common cortical surface

Key Points

- **MNI and Talairach:** Utilized for aligning and comparing volumetric brain data.
- **FSaverage:** Critical for surface-based analyses, ensuring consistent cortical surface mapping and comparison in FreeSurfer.
- **Mapping between the coordinate systems with a neural network requires a U-Net like architecture**.



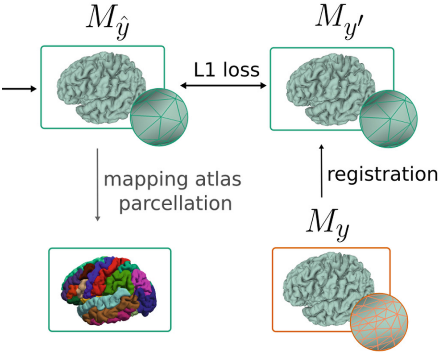


[a]

[a] Image from Probabilistic conversion of neurosurgical DBS electrode coordinates into MNI space

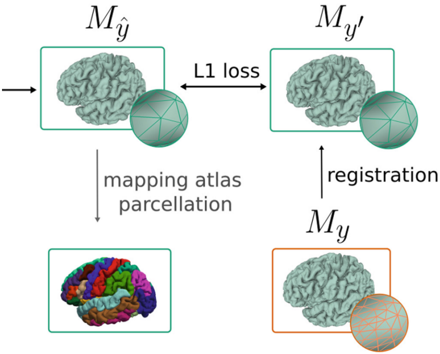
V2CC Methodology - Overview of the Process: Mesh Deformation

- **Mesh Deformation:**
    - The model (V2CC) starts with the group template `fsaverage` as its input mesh.
    - `fsaverage` template is warped to target registered ground truth surface (and L1 loss is applied during training).
    - Deformation is guided by a vertex-wise displacement field computed by the network.



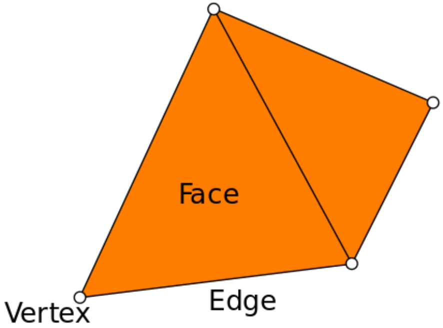
Parcellation from correspondence to fsaverage

- All compared projects are modified to deform the `fsaverage` template to the newly registered ground truth surfaces $M_{y'}$.
- Atlas Parcellation Mapping: With the vertex correspondence in place, they can directly map the atlas parcellation from the template onto the individual surfaces. This is done by transferring the pre-defined vertex labels from the template atlas to the corresponding vertices in the patient's cortical mesh.



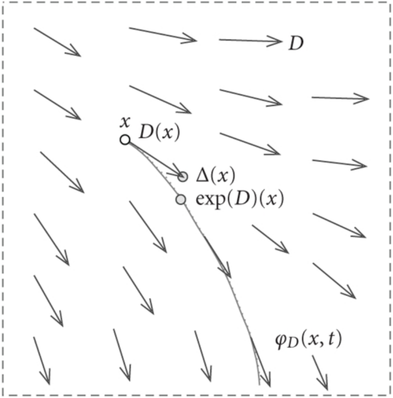
Notation - Mesh Representation

- Components: Vertices (Vx), Faces (Fx), Edges (Ex)
- Example Equation: $M_x = \{V_x \in \mathbb{R}^{n\times 3}, F_x \in \mathbb{R}^{o\times 3}, E_x \in \mathbb{R}^{r\times 2}\}$



Template Deformation

- Template Mesh: Mx = Vx, Fx, Ex
- Deformation Field: Displacement $f : \mathbb{R}^{n\times3} \rightarrow \mathbb{R}^{n\times3}$



[a]

[a] Image from: Diffeomorphic registration of images with variable contrast enhancement

Loss Function Equations

- ~~Chamfer Loss (replaced with L1)~~:

$$L_C(M_y, M_{\hat{y}}) = \frac{1}{|P_y|} \sum_{u \in P_y} \min_{v \in P_{\hat{y}}} \|u - v\|^2 + \frac{1}{|P_{\hat{y}}|} \sum_{v \in P_{\hat{y}}} \min_{u \in P_y} \|v - u\|^2$$

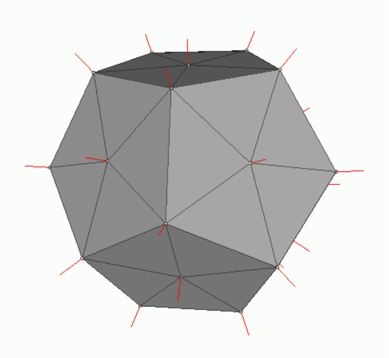
- L1 Loss in their paper:

$$L_1(M_y, M'_y) = \frac{1}{n} \sum_i |v_i - u_i|$$

- L1 Loss should be (bad notation) ($M_y \rightarrow M_{\hat{y}}$)

$$L_1(M_{\hat{y}}, M'_y) = \frac{1}{n} \sum_i |v_i - u_i|$$

Regularization Term



- Normal Consistency (face normals) (notation easily could be confused with vertex normals):

$$L_{reg}(M_{\hat{y}}) = \frac{1}{|E_{\hat{y}}|} \sum_{a,b \in E_{\hat{y}}} (1 - (\hat{n}_a \cdot \hat{n}_b))^2$$

Overall loss

- ~~Total loss (in paper) (bad notation)~~:

$$\cancel{L(M_y, M'_y) = L_1(M_y, M'_y) + \lambda L_{\text{reg}}(M_{\hat{y}})}$$

- Total loss (corrected) ($M_y \to M_{\hat{y}}$):

$$L(M_{\hat{y}}, M'_y) = L_1(M_{\hat{y}}, M'_y) + \lambda L_{\text{reg}}(M_{\hat{y}})$$

Other loss and architectural critiques

- Vox2Cortex (V2C) uses a BCE loss, which they call a Voxel loss, which is trained with deep supervision and performs a binary segmentation, which trains a UNET encoder, from which image features are extracted for the GNN.
- V2CC (new) does not mention the BCE loss or the segmentation or go into detail about its architecture, while citing Vox2Cortex as its backbone.
- Conjecture – V2CC (new) probably has repurposed the U-Net it is using from doing segmentation to doing the coordinate remaping needed for the group study for the vertex features. Or they should mention the BCE loss and how they map from sMRI to group coordinates for the GNN feature extraction.

V2CC Methodology - Takeaways

- **Key Innovation:**
  - After initial registration and training, the model produces cortical surfaces with vertex correspondence to the group `fsaverage` template without additional post-processing.
  - Streamlines the process and improves accuracy.
  - Suitable for group comparisons and atlas-based parcellation.

Experimental setup - Data Sets

- Training Data: ADNI dataset, TRT dataset, Mindboggle-101, J-ADNI.

mindboggle

ADNI
Alzheimer's Disease
Neuroimaging Initiative

TRT
test retest

Experimental setup - Evaluation Metrics

- **Chamfer Distance (cdist):** Average symmetric distance between predicted and ground truth surfaces.
- **Percentage of Self-Intersecting Faces (% SIF):** Proportion of faces intersecting each other.
- **Root-Mean-Square Deviation (RMSD):** Consistency of vertex positions in intra-subject cases.
- **Dice Overlap (Dice):** Overlap of parcellation atlas mapped onto predicted mesh.

Results Table

Method	data	fsaverage6 template						
		Right Pial			Right WM			Average
Method	data	RMSD↓	cdist↓	% SIF↓	RMSD↓	cdist↓	% SIF↓	Dice↑
V2C [3]	ADNI	1.015 ±0.496	0.437 ±0.0311	1.123	0.961 ±0.447	0.372 ± 0.030	0.185	0.762
CFPP [19]	ADNI	0.884 ±0.353	0.3314 ±0.029	**0.052**	0.778 ±0.294	0.337 ±0.031	**0.013**	0.813
Topofit [11]	ADNI	–	–	–	1.271 ±0.410	**0.180 ±0.030**	0.022	0.838
V2CC only $\mathcal{L}_1$	ADNI	**0.816 ±0.337**	**0.268 ±0.036**	2.880	**0.739 ±0.268**	**0.228 ±0.036**	0.073	**0.921**
V2CC	ADNI	0.825 ±0.360	0.285 ±0.040	1.335	0.748 ±0.285	0.231 ±0.036	0.073	**0.921**
		fsaverage template						
V2C [3]	ADNI	1.139 ±0.569	0.210 ±0.030	3.174	1.010 ±0.485	0.185 ±0.032	0.727	0.823
Topofit [11]	ADNI	–	–	–	1.326 ±0.406	**0.137 ±0.033**	**0.020**	0.871
V2CC	ADNI	**0.911 ±0.404**	**0.192 ±0.029**	**2.981**	**0.821 ±0.326**	0.186 ±0.035	0.110	**0.920**
V2C [3]	Mindb	–	0.305 ±0.045	5.372	–	0.196 ±0.023	1.272	0.780
V2CC	Mindb	-	0.305 ±0.048	4.453	–	0.204 ±0.030	0.157	0.865
V2C [3]	J-ADNI	–	0.262 ±0.046	3.578	–	0.222 ±0.078	1.063	0.803
V2CC	J-ADNI	-	0.262 ±0.048	3.614	–	0.230 ±0.079	0.140	0.913

- Good: beats others ***RMSD***, ***cdist***, ***dice***, implemented template and ground truth in other projects, multiple datasets compared, multiple measures compared
- Bad: only right hemisphere, lose in self intersections (loss and architectural tradeoffs optimized for some measures, not others)

Intra-Subject Correspondence

Intra-Subject Correspondence:

- The top box shows vertex RMSD on the TRT dataset.
- V2CC demonstrates less variance in vertex positions compared to FreeSurfer.
- This indicates that V2CC generalizes well and is more robust to subtle changes in images.

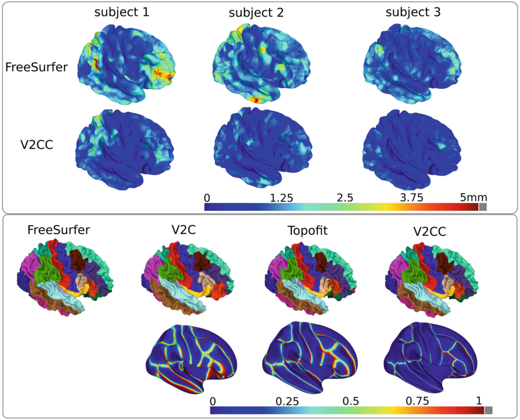
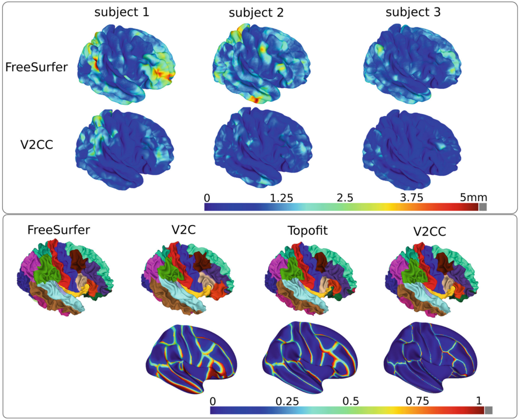


Fig. 3. Top box: vertex RMSD on the TRT dataset. Bottom box: Top: Parcellation examples on a white matter surface of the right hemisphere of an example subject from the ADNI test set. Bottom: Fraction of misclassified vertices over the test set, displayed on the smoothed fsaverage template.

Inter-Subject Correspondence

Inter-Subject Correspondence:

- The bottom box shows parcellation examples on a white matter surface of the right hemisphere of an example subject from the ADNI test set.
- The fraction of misclassified vertices over the test set is displayed on the smoothed fsaverage template.
- Parcellation errors occur mainly in boundary regions, but these regions are finer in V2CC.



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Group Study of Per-Vertex Cortical Thickness Measures

Introduction:

- This study compares cortical thickness measures between Alzheimer's disease (AD) patients and healthy controls using the ADNI test set.
- The objective is to highlight regions with significantly lower cortical thickness in AD patients.

Methods:

- Data was collected from the ADNI test set.
- Statistical analysis using t-test (one-sided) to identify regions with significant cortical thinning.

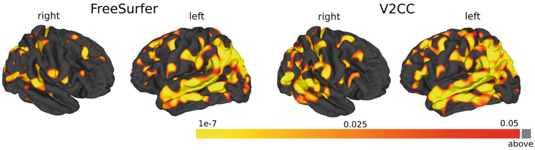


Fig. 4. Group study of per-vertex cortical thickness measures in patients with Alzheimer's disease and healthy controls on the ADNI test set. Colors indicate regions with significantly lower cortical thickness in AD subjects (t-test, one-sided). Note that our predicted meshes can be directly compared on a per-vertex basis while FreeSurfer meshes need to be inflated to a sphere and registered.

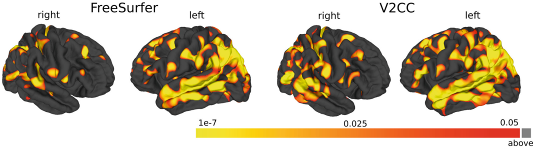
Group Study of Per-Vertex Cortical Thickness Measures

Results:

- Significant cortical atrophy observed throughout the cortex in AD patients.
- Stronger thinning in the left hemisphere, consistent with previous studies on cortical thinning in Alzheimer's disease.

Conclusion:

- The V2CC method is adequate to perform group studies.



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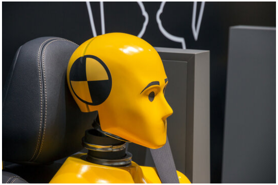
Conclusion

- Overall Impact: Efficient way to optimize models for group studies that has broad applicability to other models and research intent.
- What's missing:
  - Implementation details – github link in paper results in 404 error on 6/4/2024.
  - Implementation details – how to perform the registration for $M_{y'}$.–Author responded to email.
  - Notation – Consistency in notation between figure and equations requires advanced knowledge to error correct.
  - Methodology – How they map MRI coordinates to vertex coordinates in group template space (would be different coordinate system for the group template and the MRI).
  - Methodology – Architecture – Are they using the Unet for segmentation like its predicessor V2C does? They never mention BCE loss or segmentation. Probably using the unet to learn coordinate mapping sMRI/MNI to surface/fsaverage



The floor is open. :)