SimCortex: Collision-free Simultaneous Cortical Surfaces Reconstruction

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Abstract. Accurate cortical surface reconstruction from magnetic resonance imaging (MRI) data is crucial for reliable neuroanatomical analyses. Current methods have to contend with complex cortical geometries, strict topological requirements, and often produce surfaces with overlaps, self-intersections, and topological defects. To overcome these shortcomings, we introduce SimCortex, a deep learning framework that simultaneously reconstructs all brain surfaces (left/right white-matter and pial) from T1-weighted(T1w) MRI volumes while preserving topological properties. Our method first segments the T1w image into a nine-class tissue label map. From these segmentations, we generate subject-specific, collision-free initial surface meshes. These surfaces serve as precise initializations for subsequent multiscale diffeomorphic deformations. Employing stationary velocity fields (SVFs) integrated via scaling-and-squaring, our approach ensures smooth, topology-preserving transformations with significantly reduced surface collisions and self-intersections. Evaluations on standard datasets demonstrate that SimCortex dramatically reduces surface overlaps and self-intersections, surpassing current methods while maintaining state-of-the-art geometric accuracy.

Keywords: Cortical Surface Reconstruction · Brain Segmentation · Geometric Deep Learning · Brain MRI · 3D Deep Learning

1 Introduction

Accurate cortical surface reconstruction from MRI data enables precise measurement of key morphometric features-cortical thickness, curvature, and sulcal depth-that are invaluable for neuroimaging analyses. However, the inherent complexity of cortical geometry, compounded by partial volume effects (PVE) [1] and stringent spherical topology [5] requirements, poses substantial challenges to achieving anatomically and topologically accurate surface reconstructions.

Traditional methods, such as FreeSurfer [7], BrainSuite [17], and CIVET [13], rely on voxel-based segmentation pipelines followed by explicit mesh-based modeling. These methods are computationally intensive and require multiple hours

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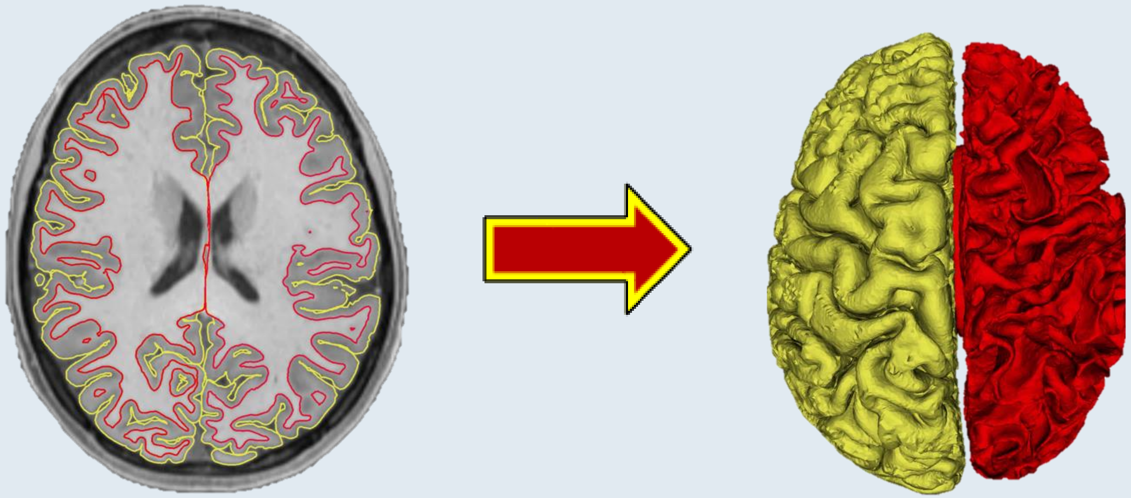
What is cortical surface reconstruction (CSR)?

Goal: Convert a brain MRI into accurate **3D meshes** of the cortex

Two surfaces per hemisphere:

- **White surface** = boundary between **Gray Matter** (cortex) and **White Matter**
- **Pial Surface:** boundary between **Gray Matter** and the **Cerebrospinal Fluid**

Total: 4 surfaces LH/RH white & pial

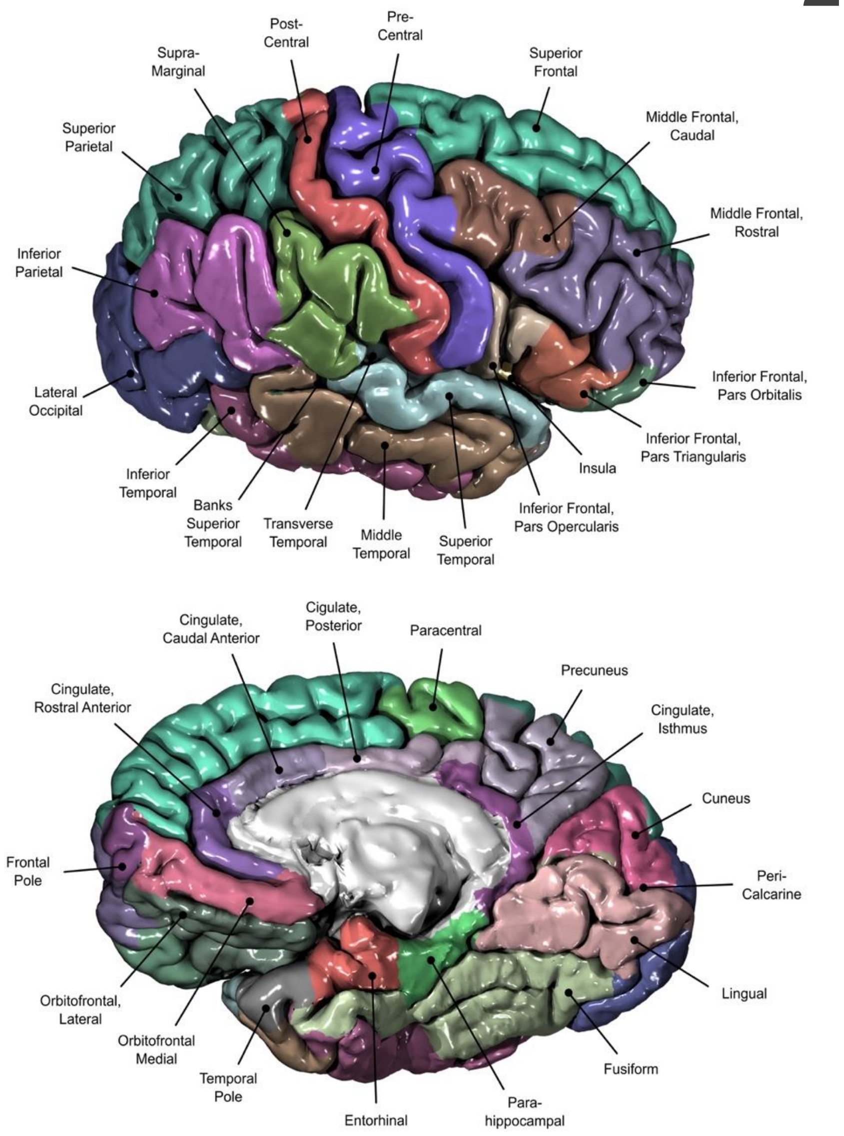


Why CSR is important!

Visualization: clear 3D view of the brain's folds

Measurement: thickness, size, and shape of the cortex

Detection: Identify and track abnormalities over time



Main Problems

Traditional (**FreeSurfer[1]**, BrainSuite[2], CIVET[3])

- **Computationally intensive:** often hours **per subject**
- **Poor scalability:** hard to use in large cohorts or time-sensitive settings

Deep learning–based

- **Independent reconstructions:** per surface/hemisphere
  no explicit coupling → **white–pial** and **left–right** collisions *(e.g., CorticalFlow[4], CortexODE[5])*
- **No topology guarantees: self-intersections/holes** can appear *(e.g., Vox2Cortex[6], V2C-Flow[7])*

SimCortex (our)

- **Jointly** estimates **all four** surfaces (LH/RH white & pial) in **one deformation space**
  preserves **geometric relationships**, **significantly reducing collisions** and **self-intersections**

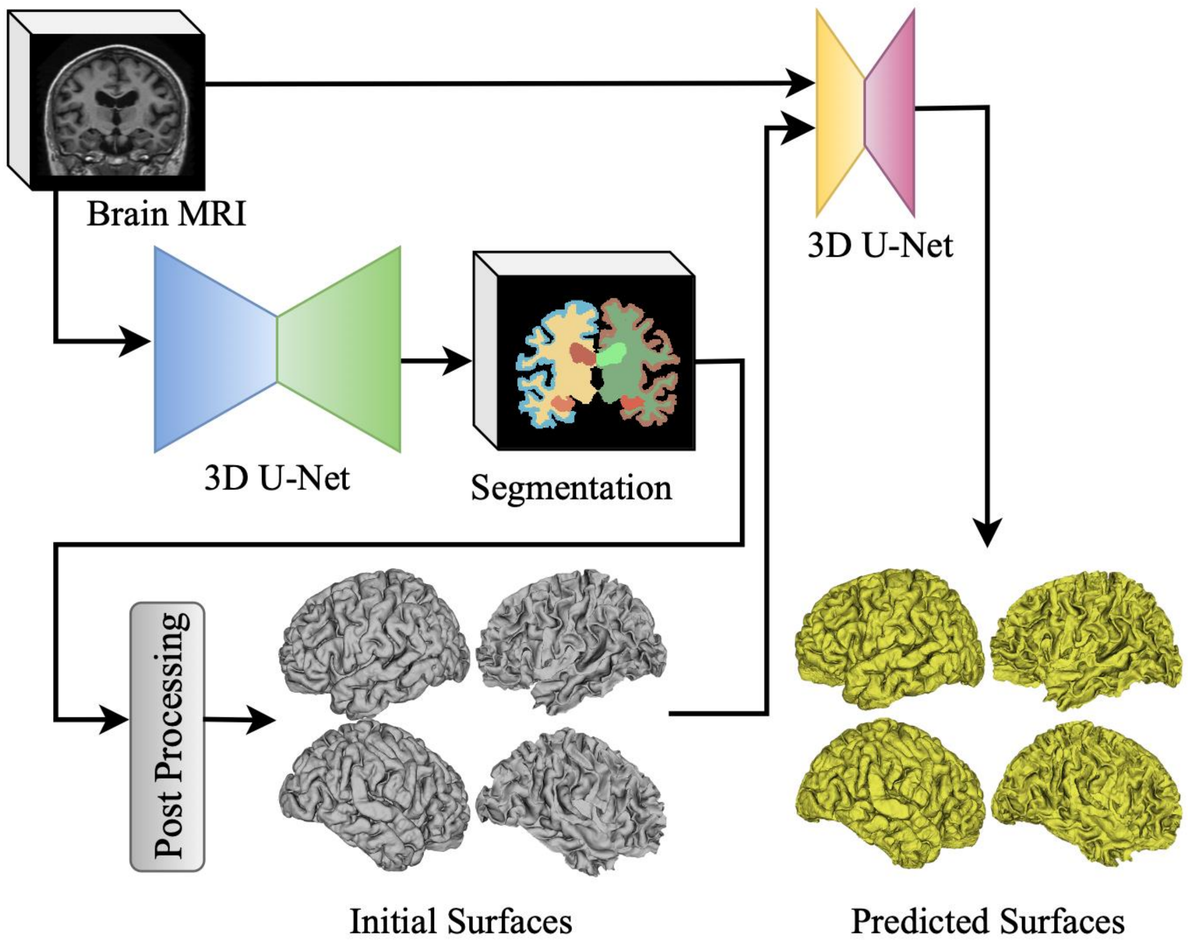
Method Overview

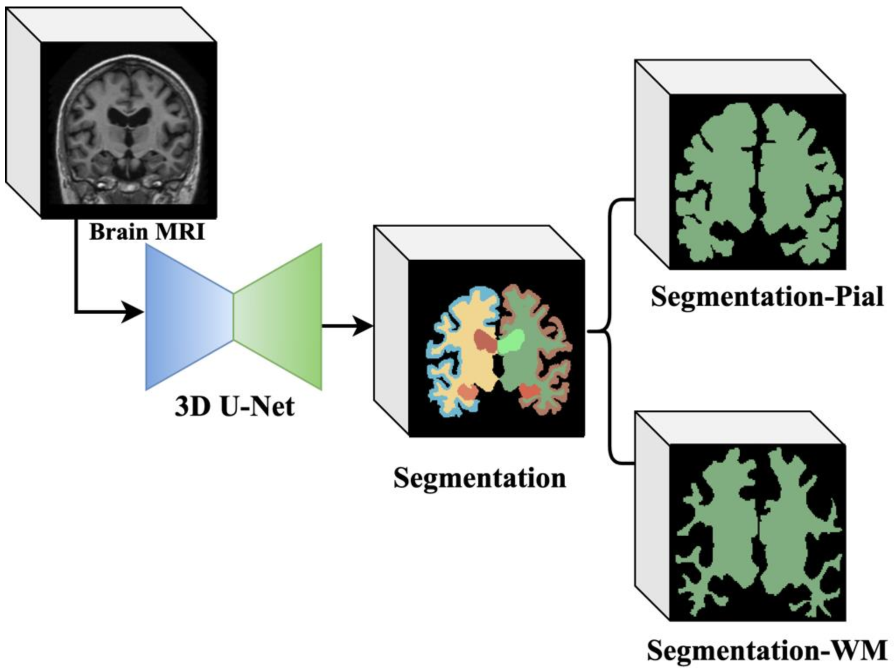
Input: T1 MRI → 3D U-Net segmentation

Init meshes: initialize 4 non-overlapping, genus-0 cortical meshes

Joint refinement: second U-Net predicts one smooth deformation

Output: four final surfaces, accurate with near-zero collisions and low self-intersections





Multi-Class Segmentation

Architecture: 3D U-Net-lite

Channels: (16, 32, 64, 128, 128) encoder levels

Parameters: ≈ 1.34 M

Output classes: 9 (BG + LH/RH WM, pial, ventricle, amyg-hip)

Optimizer: Adam ($lr = 1 \times 10^{-4}$)

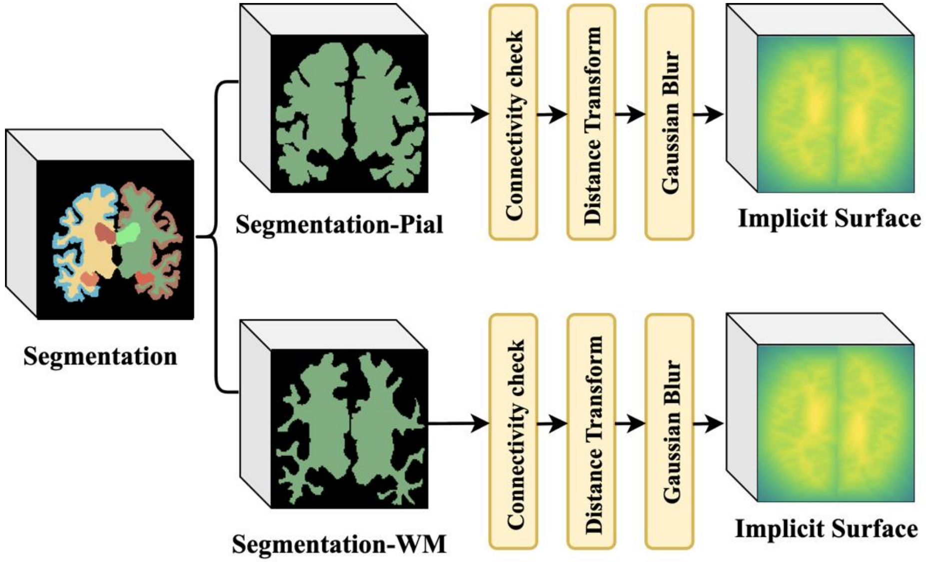
Loss: Cross-Entropy

Epochs: 1000

Device: 2 × RTX A6000 (48 GB each)

Mean Dice: 0.90 (on validation)

Make two masks per hemisphere:
Pial = WM + Cortex + Ventricles;
White = WM + Ventricles



Initial Surface Generation (SDF)

Inputs:

Pial = WM ∪ Cortex ∪ Ventricles
White = WM ∪ Ventricles

Connectivity check:

Keep **largest 3D component** (remove small islands)

Distance transform → SDF:

Signed distance to boundary
(inside **negative**, outside **positive**)

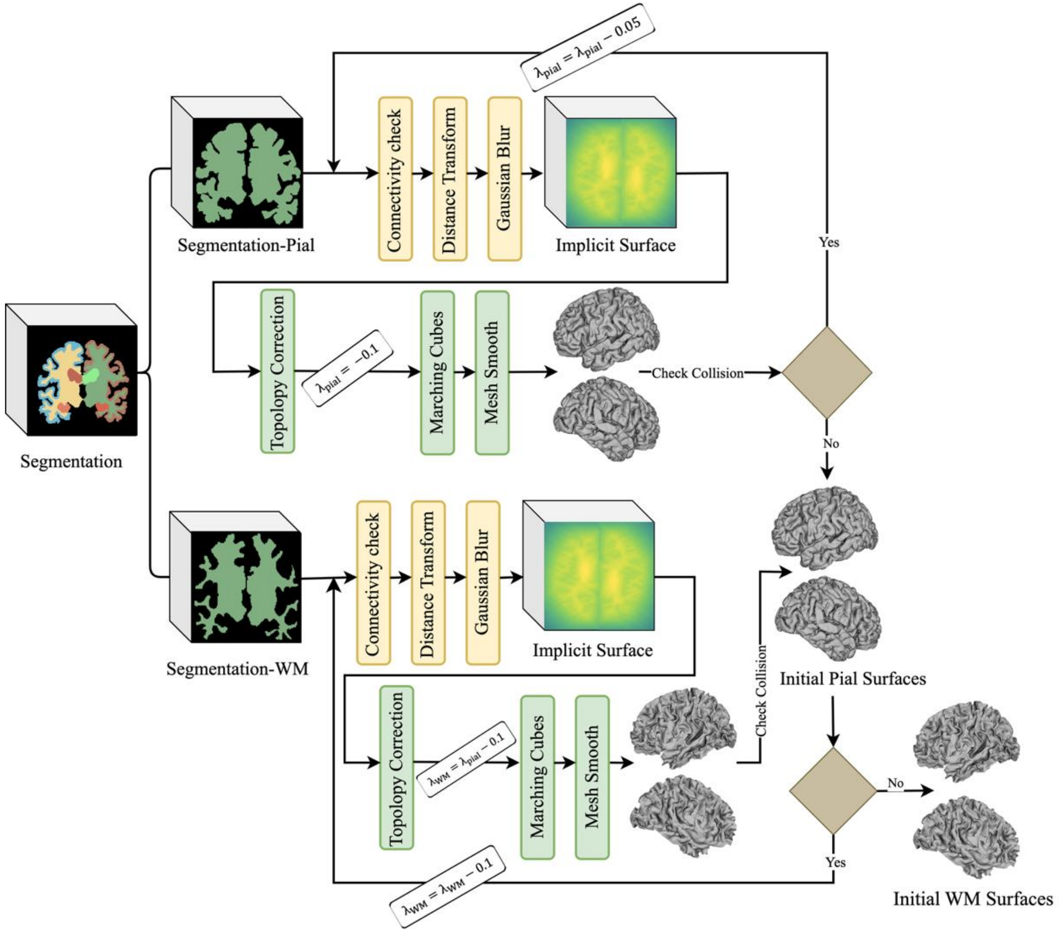
Gaussian smoothing (σ ≈ 1 mm):

Smooth the field → **stable**, **noise-robust** SDF

Why SDF?

A smooth continuous surface → choose a surface level (λ) to create a fine-detail mesh

Initial Surface Generation (Collision Checks)



Topology correction: enforce **genus-0** on the SDF

Isosurface extraction: Marching Cubes at SDF level **λ** + smoothing

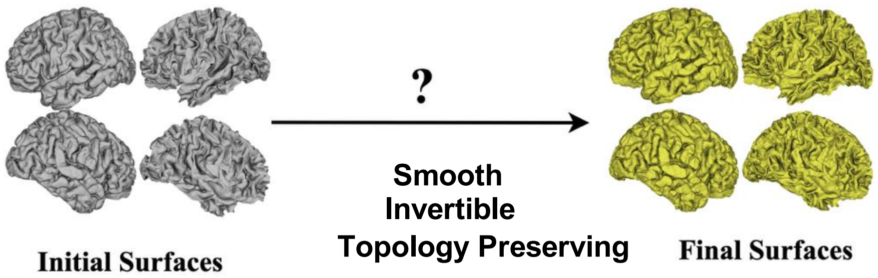
Pial first: start $\boldsymbol{\lambda_{pial} = -0.1}$ → if any **LR pial–pial** collision, step **−0.05** and re-extract

White next: $\boldsymbol{\lambda_{WM} = \lambda_{pial} - 0.1}$ → if **white–pial** or **LR white–white** collision, step **−0.1**

Collision checks: pairwise overlaps via **trimesh.CollisionManager**

Outcome: 4 non-overlapping, genus-0 meshes (LH/RH **white & pial**) ready for deformation

From Initial Templates to Final Surfaces



Start: four **collision-free, genus-0**

deformation must:

- be **invertible** → **no self-intersections**
- be **smooth/continuous** → **no tearing**
- be **topology preserving** → **no folds or holes**
- be **joint for all four surfaces** → preserves **geometric relationships**; avoids **white–pial** and **L/R** collisions

Our choice: a **diffeomorphic** deformation ϕ

Joint Diffeomorphic Deformation

Input: MNI152 T1 + **4 collision-free, genus-0** templates (LH/RH white & pial)

3D U-Net → SVFs: L=4 stationary velocity fields *(coarse→fine)*

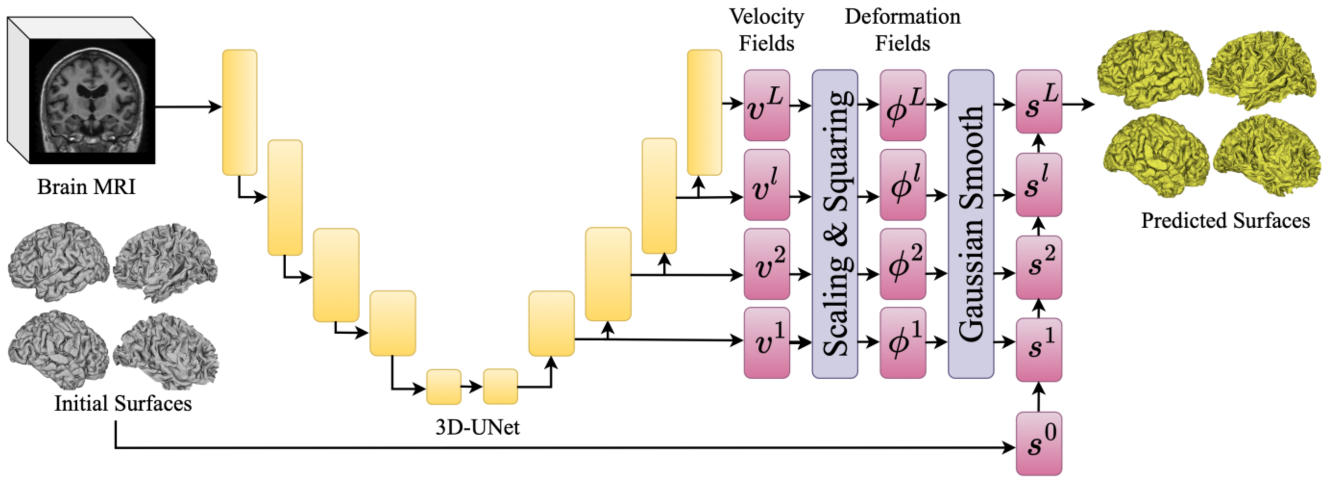
Integrate (diffeo): ϕ^{ℓ}=exp(v^{ℓ}) via **scaling-and-squaring;** compose $\phi = \phi_1 \circ \cdots \circ \phi_L$

Joint apply : same $\phi$to **all four meshes** *(one deformation space)*

Loss (multi-scale): Chamfer + Edge + Normals; sample **150k** pts/mesh

Train: AdamW 1e-4, batch **≈5**, **250 epochs (~28 h)**

Outcome: topology preserved, **near-zero collisions**, **minimal self-intersections**



Datasets

HCP[1] + OASIS-1[2] → T1w, MNI152, FreeSurfer 7.4.1 GT

- Train 356 (61 HCP, 295 OASIS)
- Val 102 (26 HCP, 76 OASIS)
- Test 51 (13 HCP, 38 OASIS)

CNP[3] → T1w, MNI152, FreeSurfer 7.4.1 GT

- Test 51 (used **only for evaluation**, not for training)

1. Human Connectome Project (HCP)
2. Open Access Series of Imaging Studies (OASIS)
3. UCLA Consortium for Neuropsychiatric Phenomics (CNP)

Evaluation Metrics

Geometric accuracy

- **Chamfer (CH)** – mean bidirectional nearest-point distance
- **ASSD** – average symmetric surface distance
- **HD** – Hausdorff distance

Topology quality

- **Self-Intersection Fraction (%SIF)** – % of faces that self-intersect

Collisions

- **Pairwise intersections** for 4 pairs: LR pial, L white–pial, R white–pial, LR white

Results: Surface Collisions

Outcome:

>90% lower collisions vs **CFPP** and **V2C**

near-zero overlaps

Table 1: Pairwise Surface Collision Percentages (%Face) for HCP-OASIS and CNP Datasets. Mean (M) and standard deviation (SD) for four surface pairs. Lower %Face indicates fewer intersections. Bold indicates best performance.

Dataset	Model	Pial L vs R		WM L vs R		L Pial vs WM		R Pial vs WM	
		M	SD	M	SD	M	SD	M	SD
HCP-OASIS	SimCortex	**0.004**	**0.005**	**0.001**	**0.002**	**0.183**	**0.157**	**0.218**	**0.177**
	CFPP	0.268	0.071	0.132	0.028	0.664	0.101	0.720	0.103
	V2C	0.188	0.078	0.159	0.034	0.728	0.074	0.806	0.076
CNP	SimCortex	**0.015**	**0.017**	**0.003**	**0.005**	**0.084**	**0.055**	**0.116**	**0.081**
	CFPP	0.286	0.064	0.113	0.039	0.559	0.077	0.574	0.100
	V2C	0.131	0.047	0.147	0.034	0.711	0.071	0.846	0.069

Results: Topology & Geometry (CNP)

Topology:

%SIF = 0.13% (≈½ **CFPP** 0.24%; ≈5× lower than **V2C** 0.68%)

Geometry (avg):

CFPP best **CH/ASSD**; **SimCortex** close; **V2C** best HD

Per-surface highlight:

SimCortex lowest **HD** on pial

Table 2: Surface Reconstruction Metrics for CNP Dataset (51 Subjects). Mean (M) and standard deviation (SD) compare SimCortex against CFPP and V2C across four cortical surfaces, with averages in the last row. Bold indicates best performance.

Surface	Model	Chamfer(mm)		ASSD(mm)		HD(mm)		SIF(%)	
		M	SD	M	SD	M	SD	M	SD
LH Pial	SimCortex	1.36	0.61	0.39	0.10	**7.19**	**1.27**	**0.03**	**0.02**
	CFPP	**1.19**	**0.65**	**0.29**	**0.13**	7.66	1.74	0.25	0.14
	V2C	1.84	0.49	0.52	0.09	7.89	0.94	1.20	0.47
LH WM	SimCortex	1.55	1.15	0.41	0.14	7.44	1.75	0.23	0.14
	CFPP	**0.91**	**0.67**	**0.26**	**0.10**	7.39	1.62	**0.07**	**0.05**
	V2C	0.95	0.33	0.34	0.07	**6.58**	**1.36**	0.15	0.15
RH Pial	SimCortex	1.44	0.66	0.40	0.10	**7.58**	**1.39**	**0.03**	**0.02**
	CFPP	**1.13**	**0.58**	**0.28**	**0.11**	7.93	1.66	0.45	0.20
	V2C	1.85	0.62	0.51	0.09	8.29	1.12	1.27	0.48
RH WM	SimCortex	1.69	1.38	0.43	0.18	7.84	2.18	0.22	0.16
	CFPP	**0.89**	**0.62**	**0.26**	**0.09**	7.68	1.57	0.18	0.11
	V2C	0.96	0.40	0.34	0.07	**6.89**	**1.66**	**0.10**	**0.11**
Average	SimCortex	1.51	0.69	0.41	0.10	7.51	1.10	**0.13**	**0.06**
	CFPP	**1.03**	**0.63**	**0.27**	**0.11**	7.66	1.43	0.24	0.10
	V2C	1.40	0.45	0.43	0.07	**7.41**	**0.90**	0.68	0.25

Results: Topology & Geometry (HCP–OASIS)

Topology:

%SIF = 0.04% (≈⅓ **CFPP** 0.13%; **>10×** lower than **V2C** 0.54%)

Geometry (avg):

CFPP best **CH/ASSD**
SimCortex close

HD (avg): V2C lowest
SimCortex 6.86; **CFPP** 6.88
(all very close)

Per-surface highlight:

SimCortex lowest **CH** on **LH** pial and lowest **%SIF** on both pial

Table 3: Surface Reconstruction Metrics for HCP-OASIS Dataset (51 Subjects). Mean (M) and standard deviation (SD) compare SimCortex against CFPP and V2C across four cortical surfaces, with averages in the last row. Bold indicates best performance.

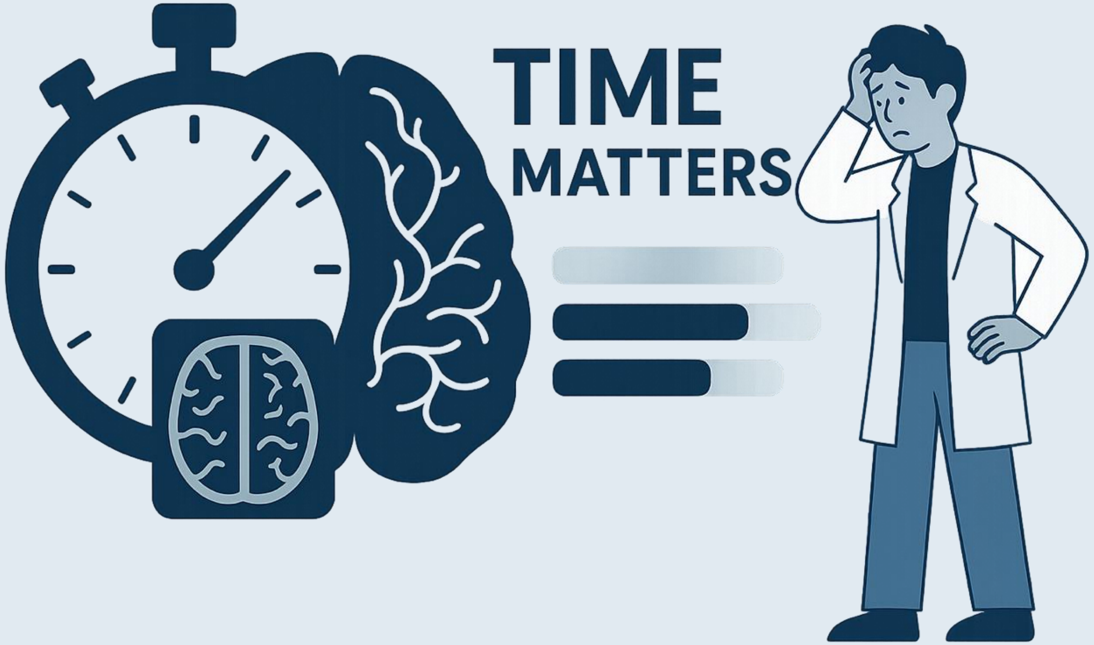
Surface	Model	Chamfer(mm)		ASSD(mm)		HD(mm)		SIF(%)	
		M	SD	M	SD	M	SD	M	SD
LH Pial	SimCortex	**1.10**	**0.27**	0.33	0.08	7.15	1.30	**0.01**	**0.01**
	CFPP	1.13	0.32	**0.32**	**0.11**	**6.79**	**1.23**	0.15	0.11
	V2C	1.60	0.29	0.49	0.07	7.49	1.01	1.02	0.69
LH WM	SimCortex	1.26	2.37	0.32	0.21	6.52	2.36	0.08	0.07
	CFPP	**0.79**	**0.14**	**0.24**	**0.05**	6.89	1.46	**0.06**	**0.06**
	V2C	0.83	0.09	0.32	0.05	**5.66**	**1.00**	0.06	0.06
RH Pial	SimCortex	1.11	0.20	0.33	0.05	7.41	1.78	**0.01**	**0.01**
	CFPP	**1.09**	**0.15**	**0.31**	**0.06**	**6.90**	**0.91**	0.23	0.15
	V2C	1.55	0.17	0.48	0.04	7.63	0.78	1.00	0.71
RH WM	SimCortex	0.98	0.51	0.30	0.09	6.37	2.17	0.07	0.09
	CFPP	**0.80**	**0.15**	**0.25**	**0.06**	6.92	1.47	0.10	0.08
	V2C	0.83	0.10	0.32	0.05	**5.53**	**0.94**	**0.06**	**0.06**
Average	SimCortex	1.11	0.62	0.32	0.07	6.86	1.16	**0.04**	**0.03**
	CFPP	**0.95**	**0.15**	**0.28**	**0.06**	6.88	0.83	0.13	0.08
	V2C	1.21	0.13	0.40	0.04	**6.58**	**0.57**	0.54	0.35

Computation Time

Training: 250 epochs ≈ **28 hours** (our hardware)

Inference (per subject, all 4 surfaces):

- **SimCortex: 0.28 s** (simultaneous LH/RH white & pial)
- **CFPP: 0.70 s** (0.35 s LH + 0.34 s RH; processed separately)



Visual Analysis (Geometry Accuracy)

SimCortex:

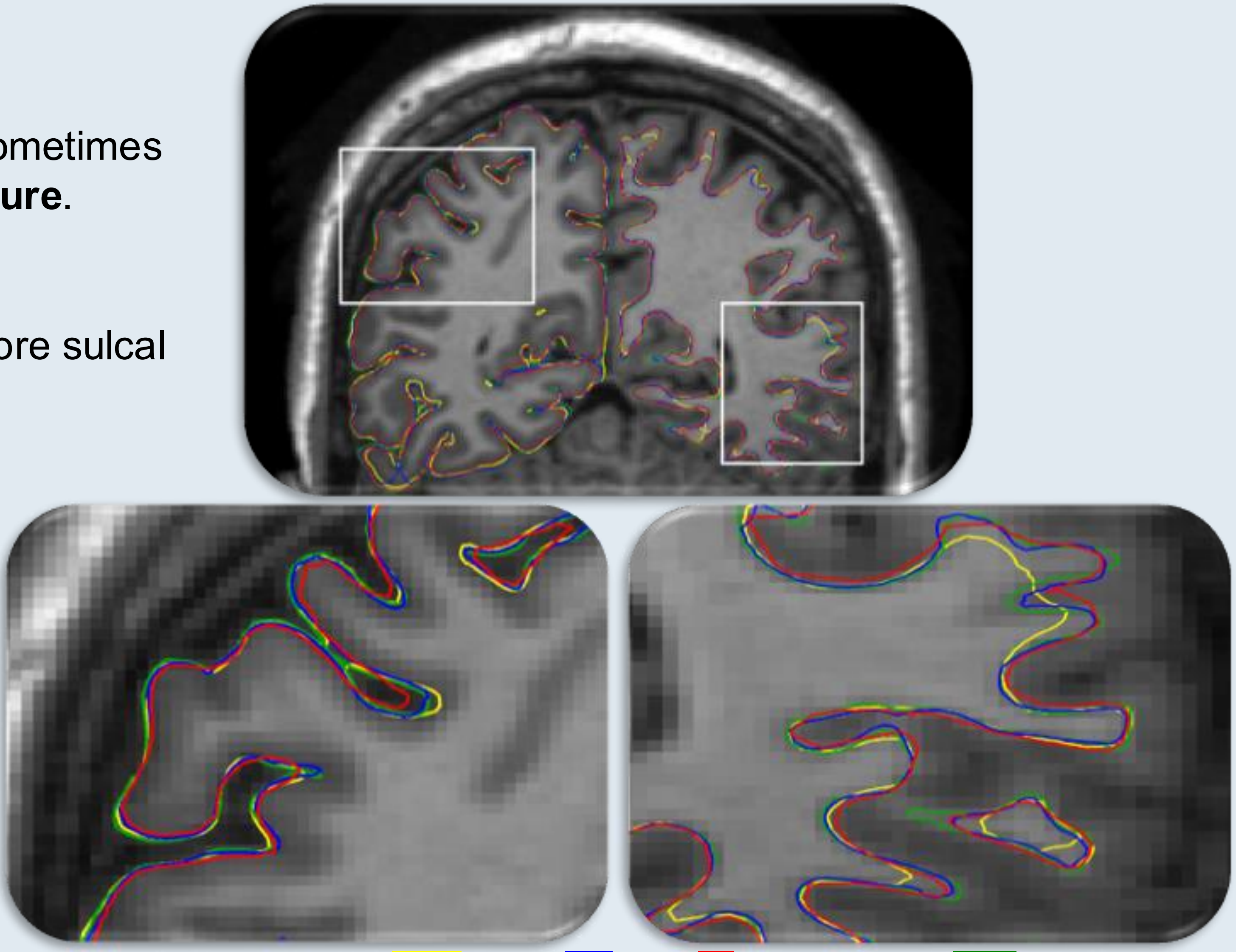
deeper sulci in some regions; sometimes **smoother/less detailed curvature**.

CFPP:

generally **closest geometry**, more sulcal detail (esp. **white matter**).

V2C:

overall **less precise** than CFPP/SimCortex.



SimCortex (yellow), CFPP (blue), V2C (red), and ground truth (green)

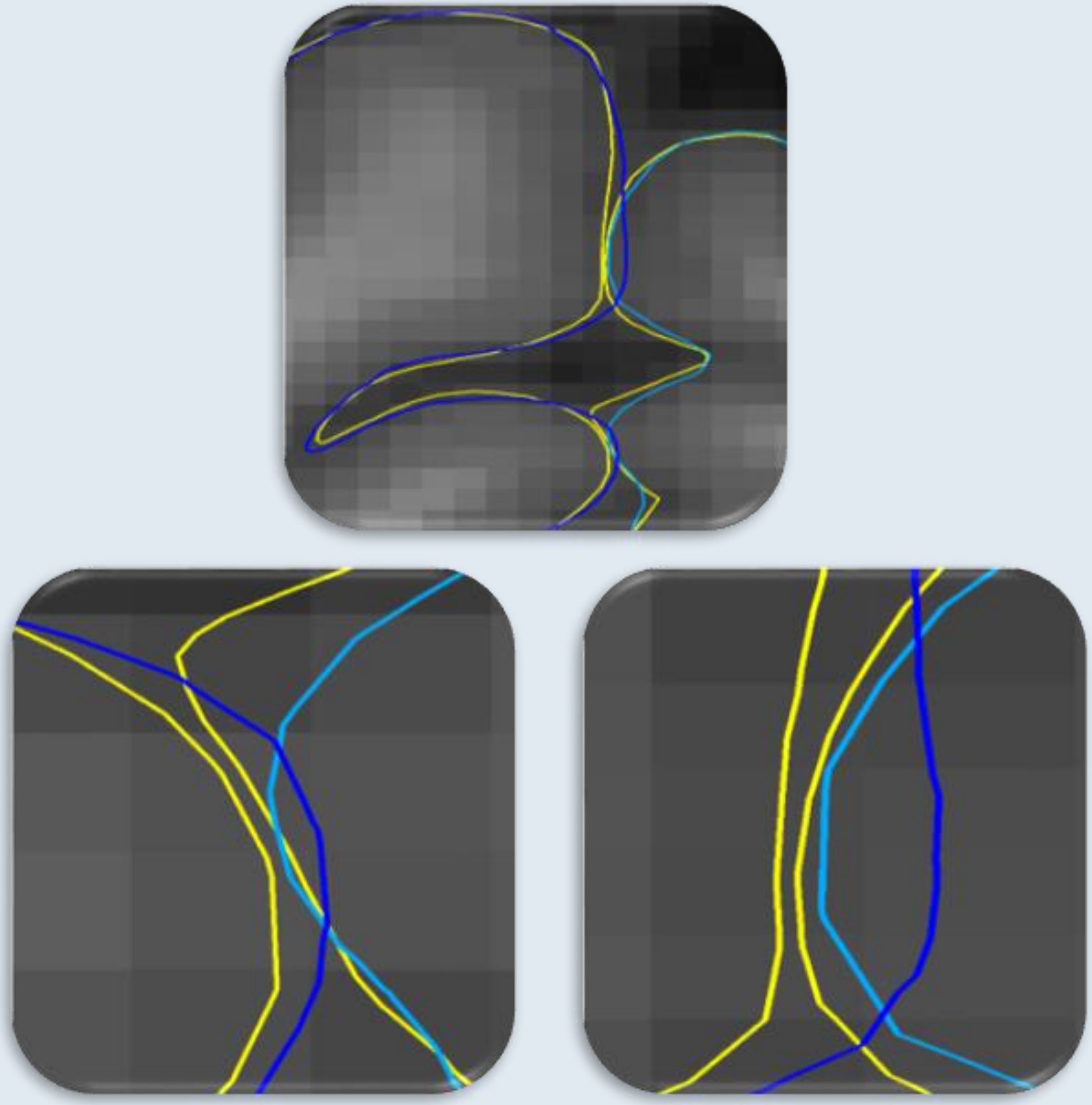
Visual Analysis (Collisions)

SimCortex (yellow):

avoids left–right collisions.

CFPP (dark/light blue L/R):

visible LR collisions.



Conclusion

What we built:

SimCortex reconstructs all four cortical surfaces jointly using a single diffeomorphic deformation, starting from collision-free, genus-0 templates

Key results:

>90% fewer collisions, lowest %SIF, competitive CH/ASSD/HD, ~0.28 s/subject

Why it matters:

Topology-correct, near-zero-collision surfaces → more reliable thickness/curvature and scalable studies

Limitation:

Slightly smoother/shallower white-matter sulci in some regions.

Why: In tight white–pial gaps, λ-tuning to avoid collisions pulls the white surface inward, and smoothing reduces fine detail

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THANK YOU!