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CorticalFlow^{++}: Boosting Cortical Surface Reconstruction Accuracy, Regularity, and Interoperability

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Source Code & Trained Models

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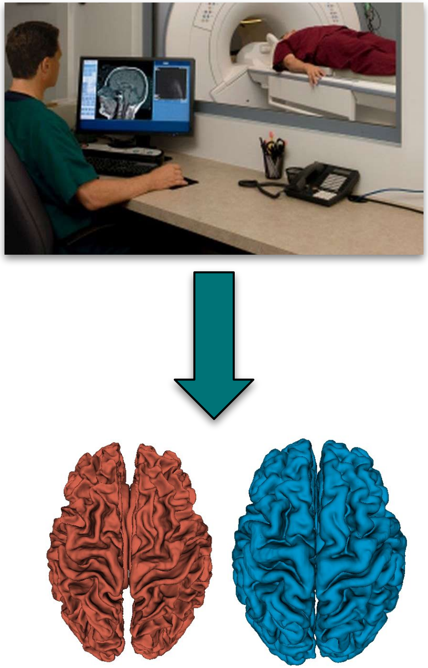
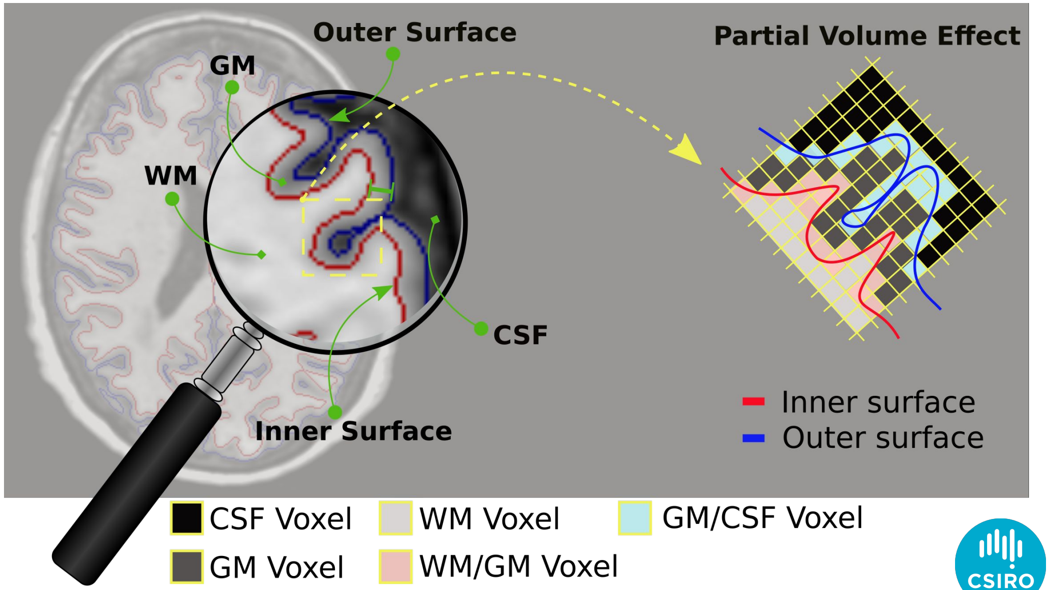
Cortical Surface Reconstruction From MRI (CSR)

"The diagnosis, prognosis, and study of neurodegenerative diseases, as well as many psychological disorders, rely on the analysis of *in vivo* measurements on the **cerebral cortex** using magnetic resonance imaging (MRI)."

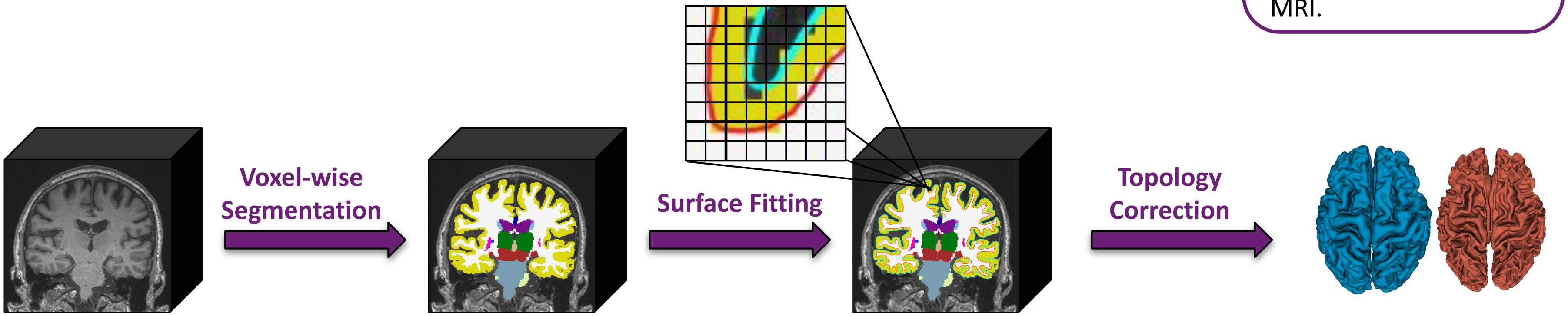




Existing Approaches

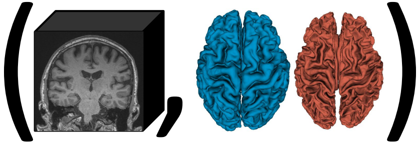
FreeSurfer V6 takes more than 6 hours per scan depending on the hardware used and the quality of the input MRI.

→ Traditional CSR pipelines (Ex: FreeSurfer, CVIET, BrainSuite …):

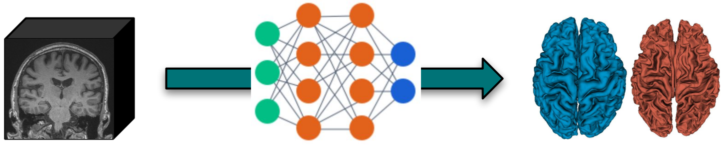


→ Learning-based approaches (Ex: DeepCSR, Vox2Mesh, PialNN):

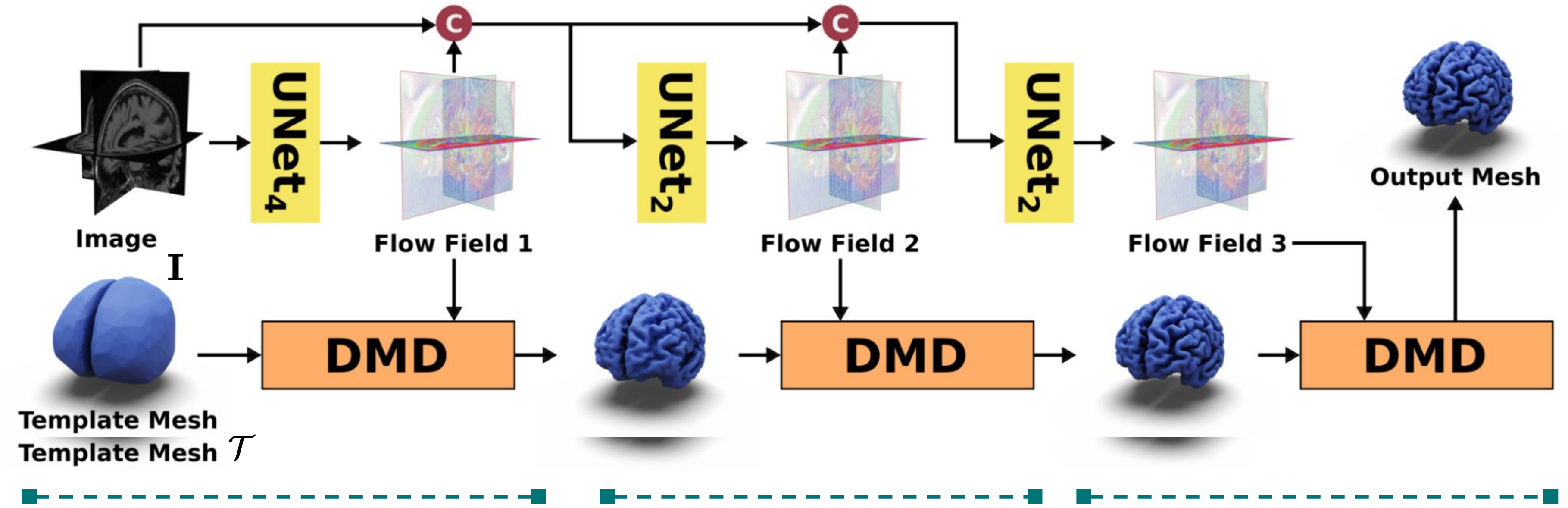
From hours to seconds



i=1, …, N



CorticalFlow



$$\mathrm{CF}^{1}_{\theta_1}(\mathbf{I},\mathcal{T}_1) = \mathrm{DMD}\Big(\mathrm{UNet}^{1}_{\theta_1}(\mathbf{I}),\mathcal{T}_1\Big)$$

$$\mathrm{CF}^{i+1}_{\theta_{i+1}}(\mathbf{I},\mathcal{T}_{i+1}) = \mathrm{DMD}\Big(\mathrm{UNet}^{i+1}_{\theta_{i+1}}(\mathbf{U}_1^\frown\cdots\mathbf{U}_i^\frown\mathbf{I}),\mathrm{CF}^{i}_{\theta_i}(\mathbf{I},\mathcal{T}_{i+1})\Big)$$

Lebrat, Leo, et al. Corticalflow: A diffeomorphic mesh transformer network for cortical surface reconstruction. In Advances in Neural Information Processing Systems, 2021.

Our goal is to improve CorticalFlow's **accuracy, regularity, and interoperability** with existing surface analysis tools, but **without** severely **degrading** its **inference time and GPU memory** consumption.

(1) Higher Order ODE Solver (2) Smooth Templates (3) White To Pial Surface Morphing

1) Higher Order ODE Solve

In order to deform the template mesh while **preserving Its topology**, DMD modules compute per vertex diffeomorphic mappings $\mathbf{\Phi}$ from the predicted flow field **U** by solving the **flow ODE**,

$$\frac{d\Phi(s;\mathbf{x})}{ds} = \mathbf{U}\left(\Phi(s;\mathbf{x})\right), \text{with} \quad \Phi(0;\mathbf{x}) = x$$

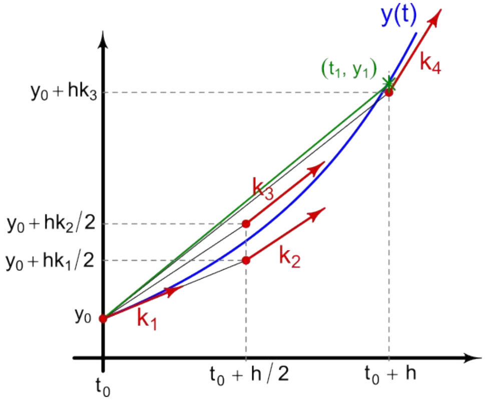
CorticalFlow uses the forward **Euler method,**

$$\hat{\Phi}(h,\mathbf{x}) = \mathbf{x} + h\mathbf{U}(\mathbf{x}),$$

While **CorticalFlow++** uses the **RK4 method**:

$$\hat{\Phi}(h,\mathbf{x}) = \mathbf{x} + \frac{1}{6}[k_1 + 2k_2 + 2k_3 + k_4]$$

where $k_1 = \mathbf{U}(\mathbf{x})$ $k_2 = \mathbf{U}\left(\mathbf{x} + h\frac{k_1}{2}\right)$ $k_3 = \mathbf{U}\left(\mathbf{x} + h\frac{k_2}{2}\right)$ $k_4 = \mathbf{U}(\mathbf{x} + hk_3)$



While **Euler's** error is only **linearly** reduced with the step size, **RK4's** error is **quartically** reduced providing **more accurate solutions** at a given number of integration steps !!!

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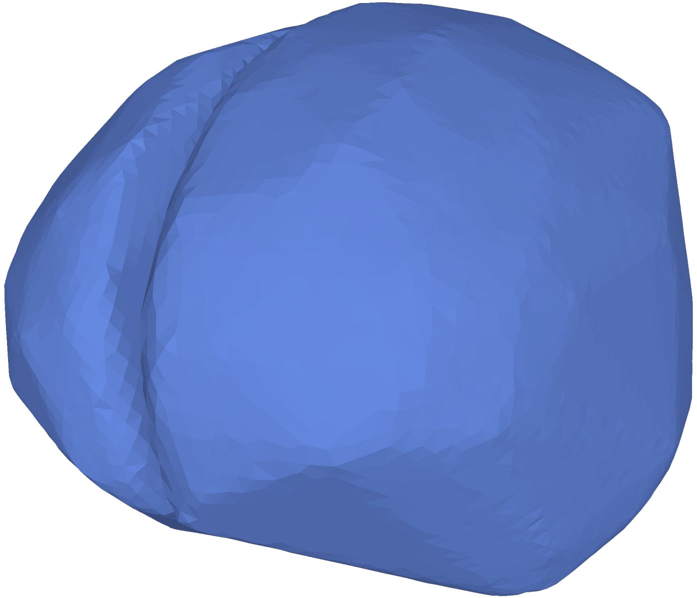
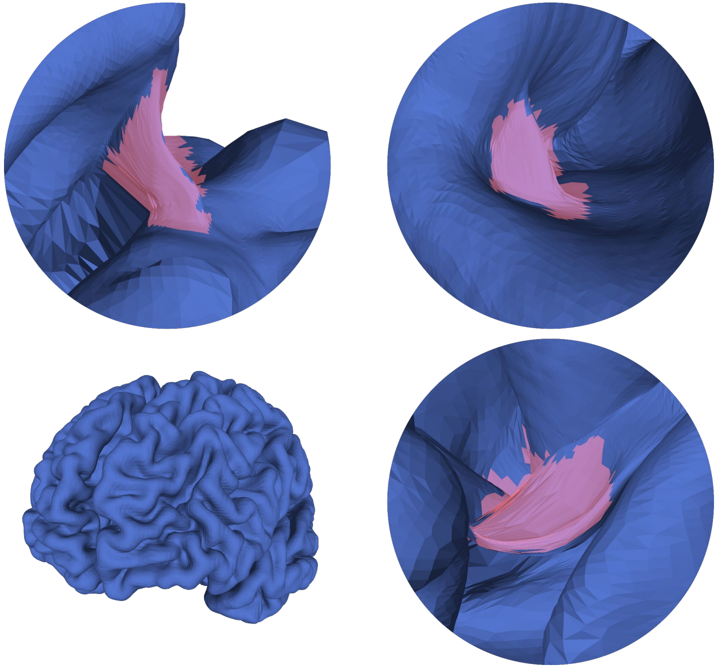
2) Smooth Templates

CorticalFlow's template consists of the **convex-hull** of all cortical surface meshes in the training set.



Present large gaps and sharp edges



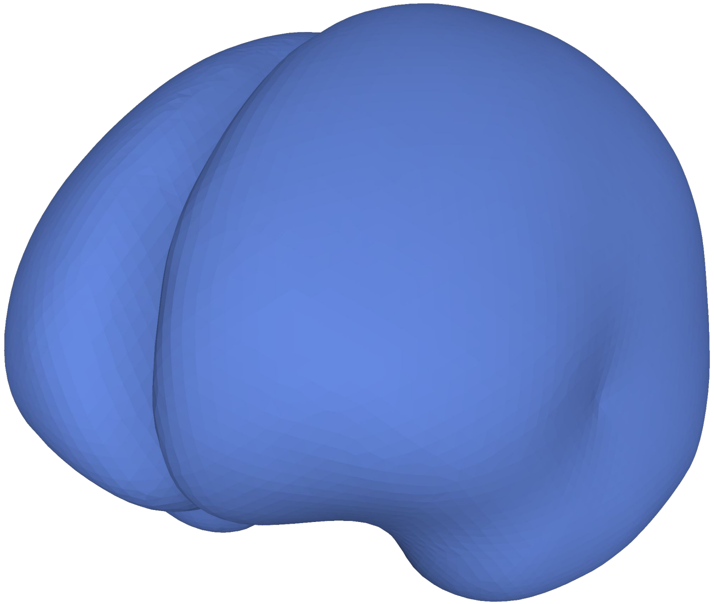
Artifacts in reconstructed mesh

2) Smooth Templates

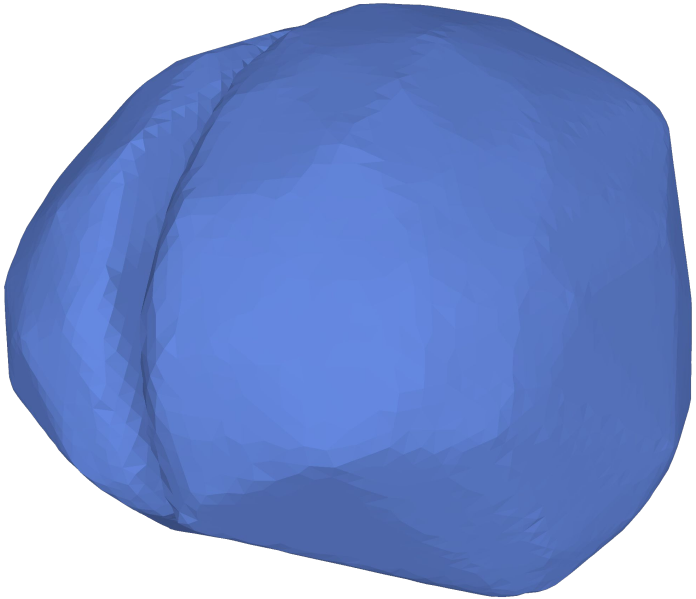
While, **CorticalFlow++** proposes a simple routine to produce smooth template mesh with spherical topology tightly wrapping all training set.

Procedure:

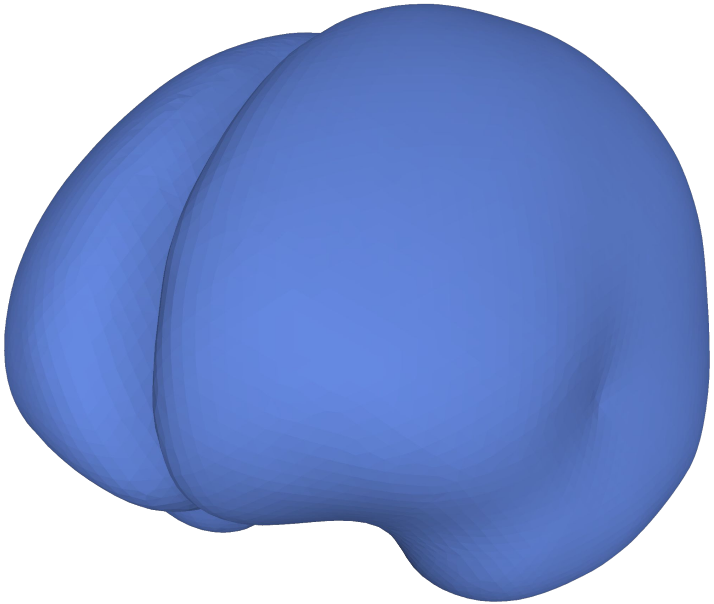
1. Compute a **signed distance grid** for every training mesh.
2. Threshold and compute the **binary union** of these grids.
3. Use **marching cubes** algorithm to obtain a coarse mesh.
4. Smooth the coarse mesh by applying **laplacian smoothing**.
5. Remesh using **delaunay triangulation**.



2) Smooth Templates



CorticalFlow's Template

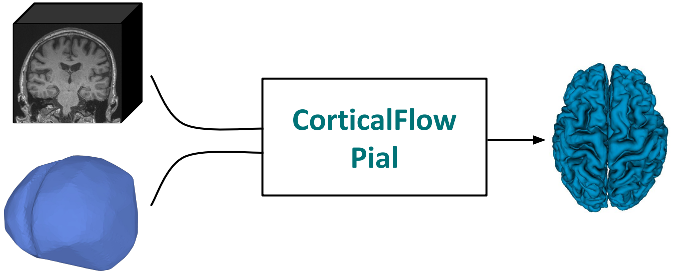


CorticalFlow++'s Template

A "**tighter**" **template without sharp edges** makes our reconstruction problem easier leading to **more regular** reconstructed surfaces **without mesh artifacts.**

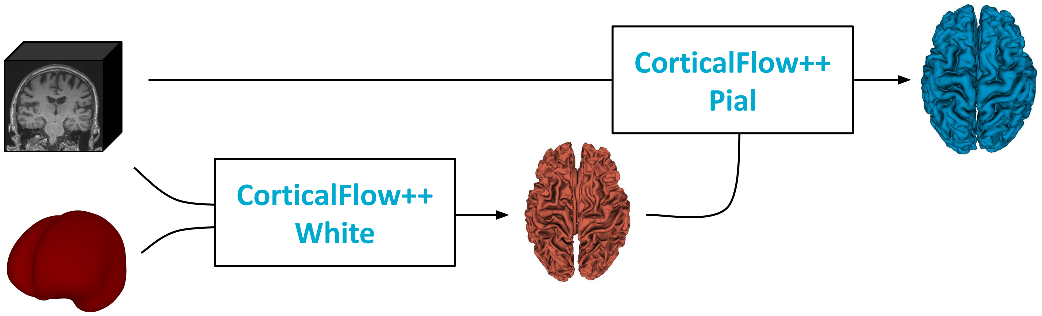
3) White To Pial Surface Morphing

CorticalFlow predicts surfaces by deforming separate **template meshes** leading to reconstructed meshes **without a one-to-one mapping** between the vertices in the white and pial surfaces.



- Not useful for many post processing tools like cortical thickness estimation [1].
- Does not exploit the natural anatomical agreement between pial and white surfaces [2].

Instead, **CorticalFlow++** predicts pial surfaces by deforming its corresponding **predicted white surface.**



CorticalFlow++ provides more **interoperability** with existing surface analysis tools by reconstructing pial and white surfaces **with a one-to-one mapping** on their vertices.

[1] - Das, Sandhitsu R., et al. "Registration based cortical thickness measurement." Neuroimage 45.3 (2009): 867-879.
[2] - Ma, Q., et al.: Pialnn: A fast deep learning framework for cortical pial surface reconstruction. In: International Workshop on Machine Learning in Clinical Neuroimaging. (2021)

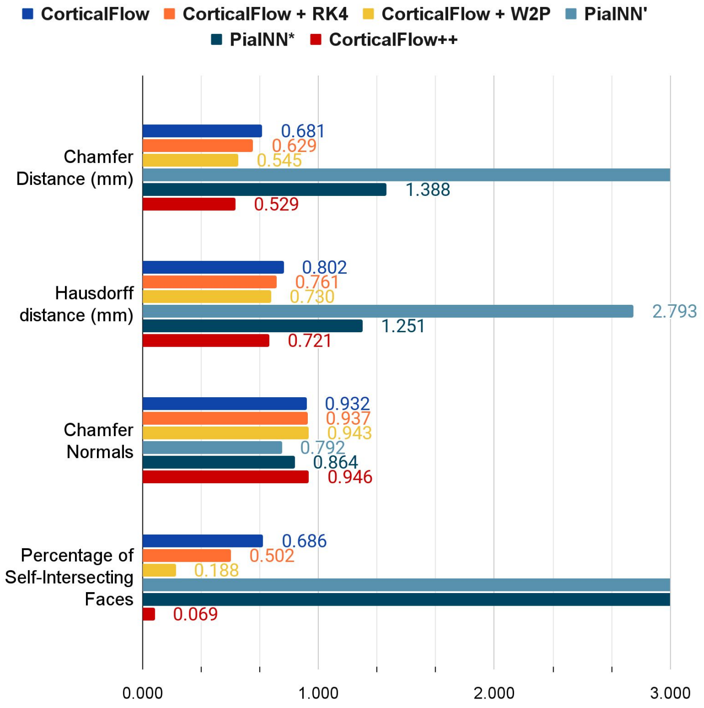
Experiments

- **Dataset:**
  - CSR benchmark proposed in [1].
    - 3876 MRI images from **ADNI study** and pseudo ground truth surfaces generated with the **FreeSurfer V6.0 cross-sectional** pipeline.
  - Evaluation on **OASIS3 MRIs** with models trained only on the CSR benchmark.
- **Baselines:**
  - CorticalFlow [2]
  - PialNN [3] :
    - PialNN' - Trained weights downloaded from [4]
    - PialNN* - A model trained by ourselves on CSR benchmark data using the source code available in [4].
- **Metrics:**
  - Geometric accuracy: Chamfer distance, Hausdorff distance, and Chamfer normals.
  - Surface regularity: Percentage of self-intersecting faces computed using **PyMeshLab**.
  - Time and space complexity: Average time (in seconds) and GPU memory footprint (in GB) to reconstruct the **four cortical surfaces**.

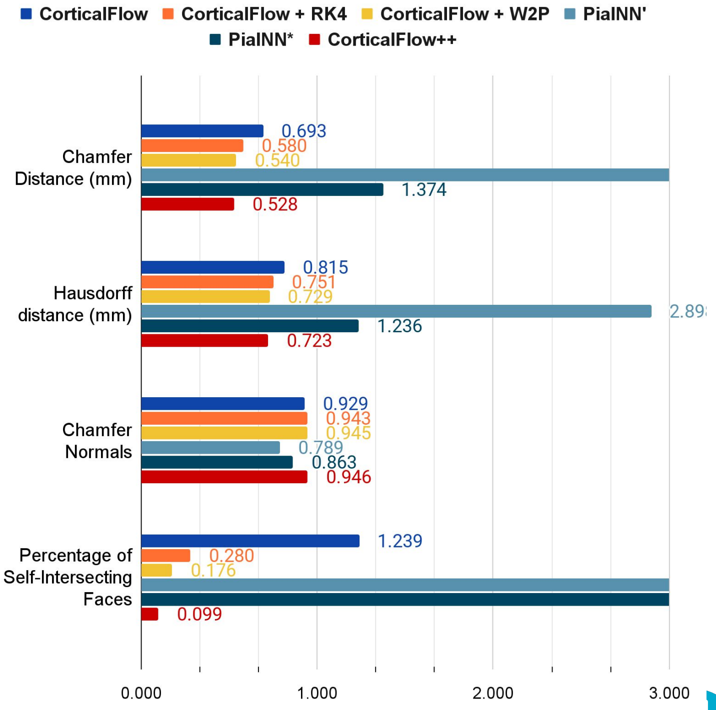
[1] - Santa Cruz et al. DeepCSR: A 3d deep learning approach for cortical surface reconstruction. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021.
[2] - Lebrat, Leo, et al. Corticalflow: A diffeomorphic mesh transformer network for cortical surface reconstruction. In Advances in Neural Information Processing Systems, 2021.
[3] - Ma, Q., et al.: Pialnn: A fast deep learning framework for cortical pial surface reconstruction. In: International Workshop on Machine Learning in Clinical Neuroimaging. (2021)
[4] - PialNN Github Repository: https://github.com/m-qiang/PialNN

ADNI - Benchmark

Left Pial Surface:

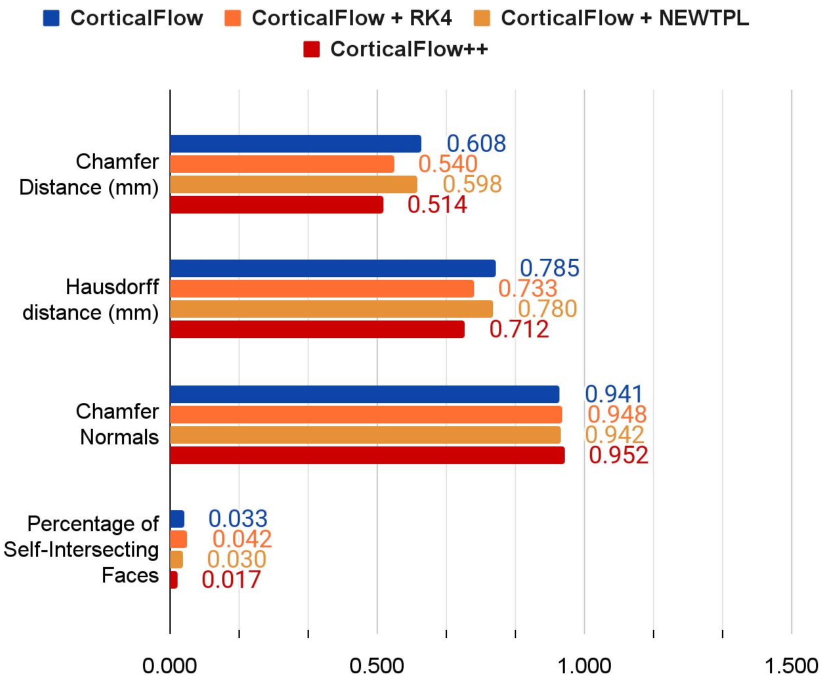


Right Pial Surface:

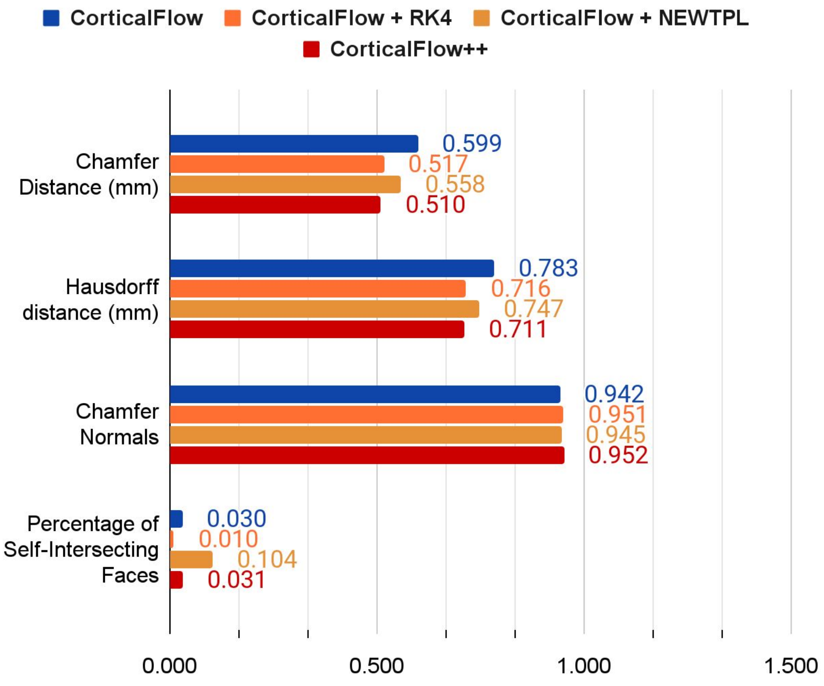


ADNI - Benchmark

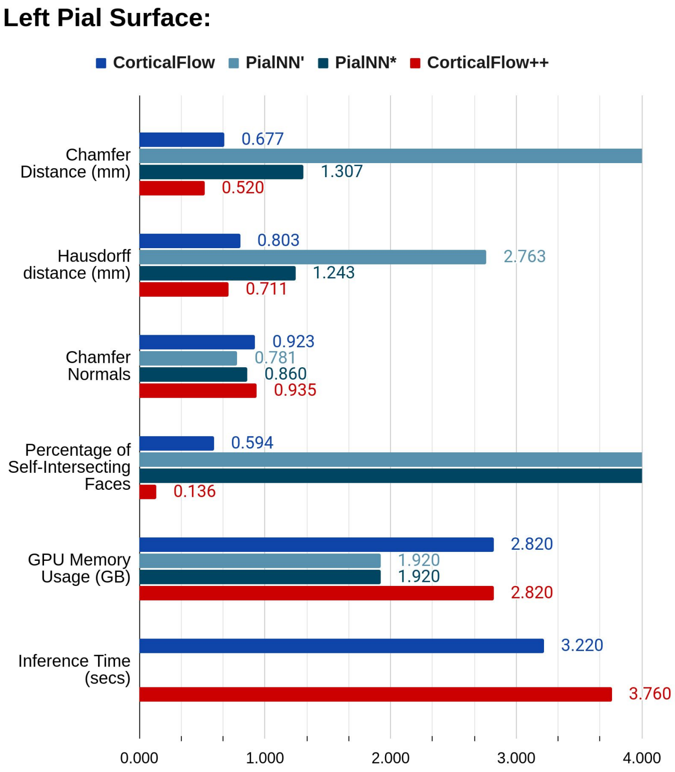
Left White Surface:

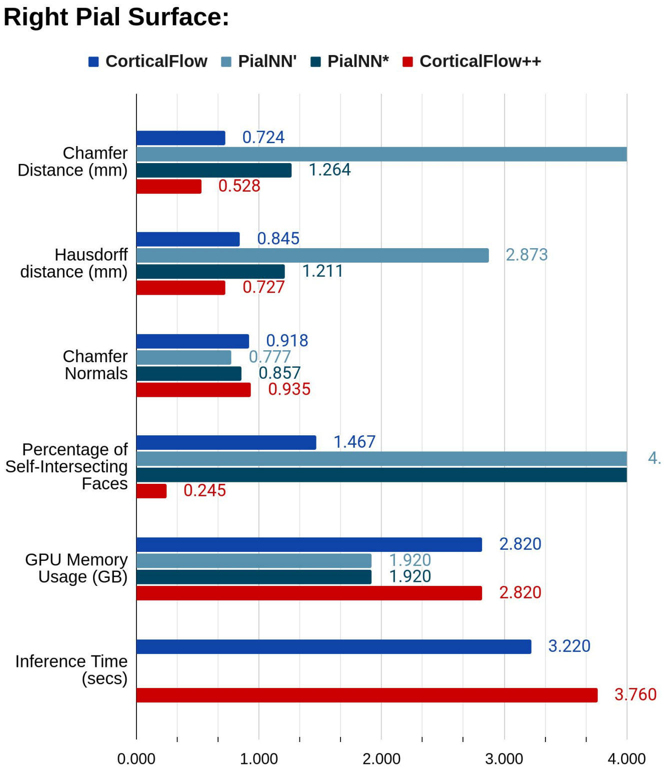


Right White Surface:



OASIS3 (Out-of-train distribution)





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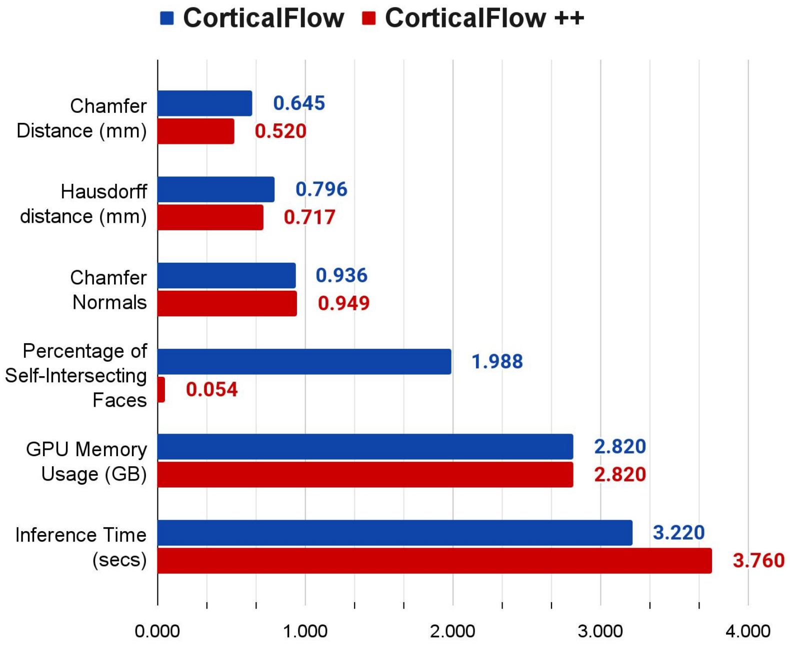
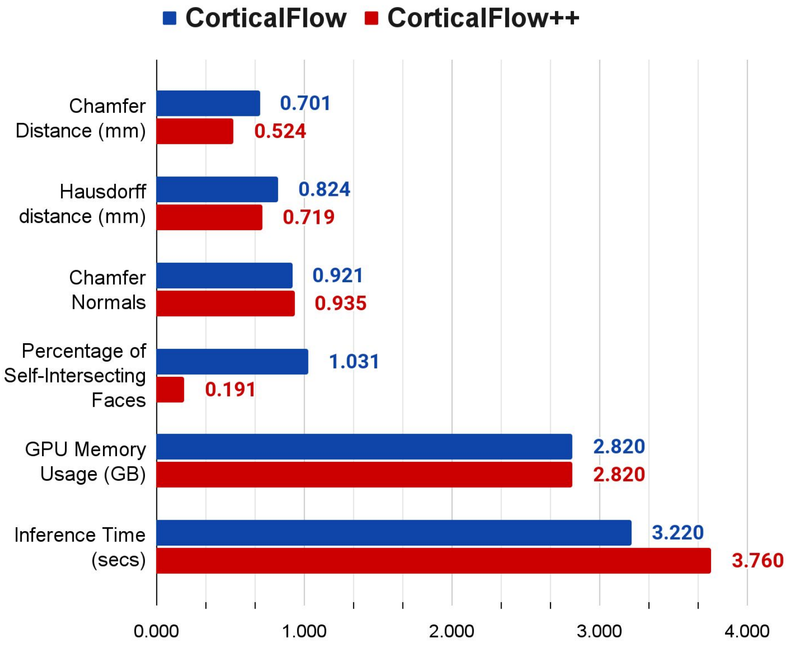
Results Summary

ADNI Benchmark

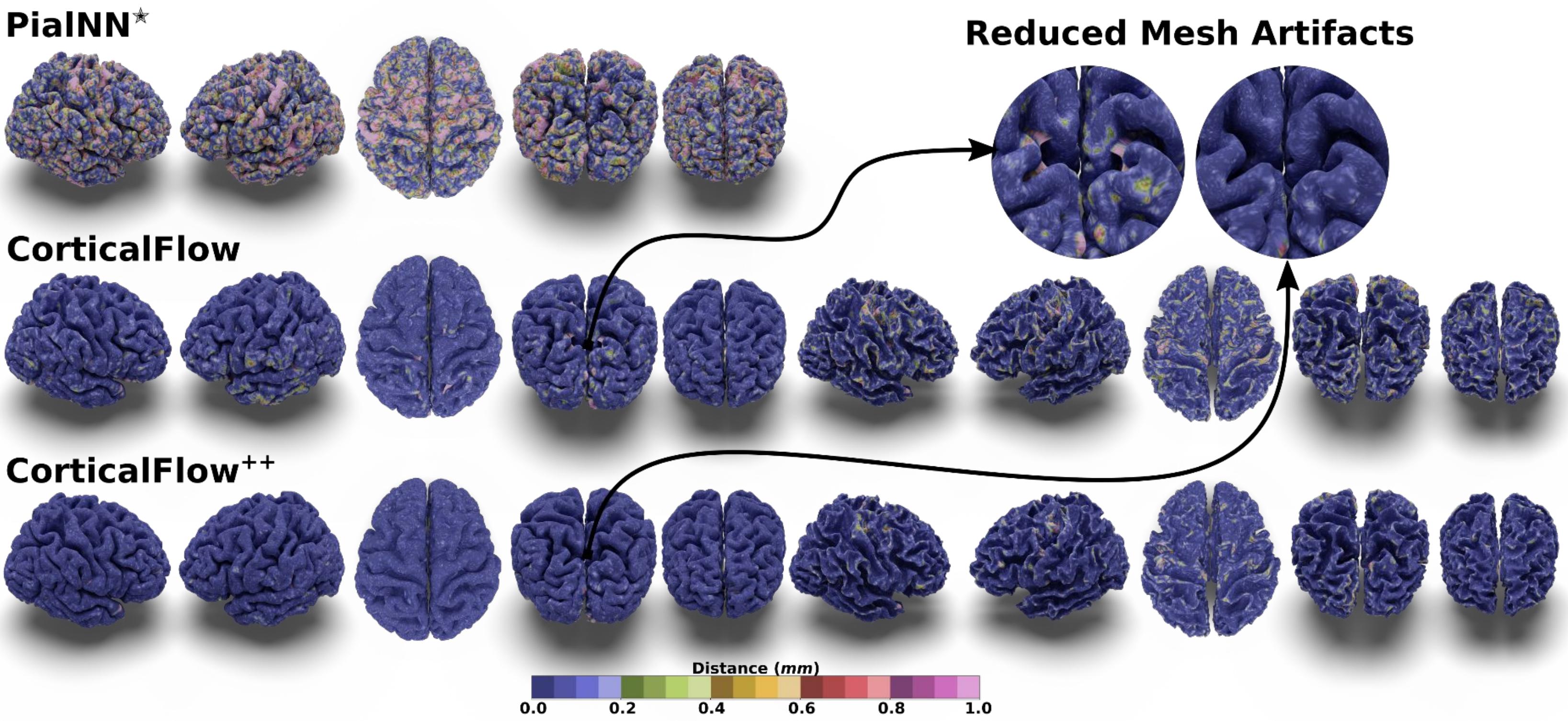


OASIS3 (Out-Of-Train Distribution)

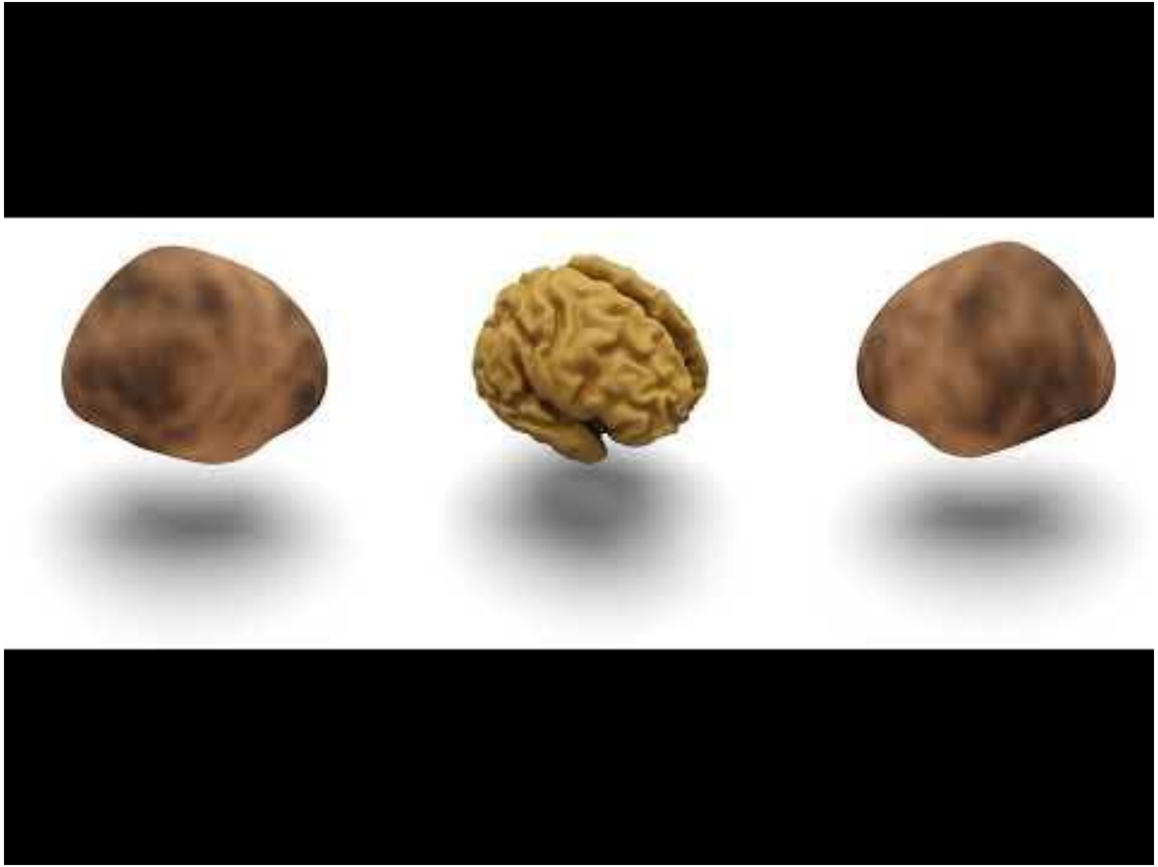


CorticalFlow++ produces more accurate and regular surfaces than **CorticalFlow**, while adds only half a second to the final surface reconstruction time and keeps the same GPU memory budget.

Qualitative Results



Qualitative Results



Conclusion

This paper …

- tackles some limitations of CorticalFlow, the current state-of-theart model for Cortical surface reconstruction from MRI, in order to improve its accuracy, regularity, and interoperability without sacrificing its computational requirements for inference (reconstruction time and maximum GPU memory consumption).
- The resulting method, CorticalFlow++, achieves state-of-the-art performance on geometric accuracy and surface regularity while keeping the GPU memory consumption constant and adding less than a second to the entire surface reconstruction process.

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