



Australia's National Science Agency

CorticalFlow: A Diffeomorphic Mesh Transformer for Cortical Surface Reconstruction

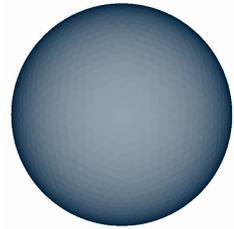
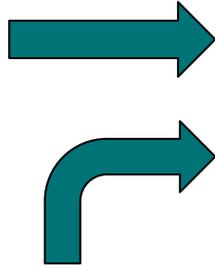
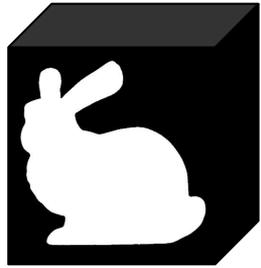
Leo Lebrat, **Rodrigo Santa Cruz**, Frederic de Gournay, Darren Fu, Pierrick Bourgeat, Jurgen Fripp, Clinton Fookes, and Olivier Salvado

THE AUSTRALIAN
EOHEALTH
RESEARCH CENTRE

QUT Queensland
University
of Technology



Regular Surface Reconstruction From Volumetric Images

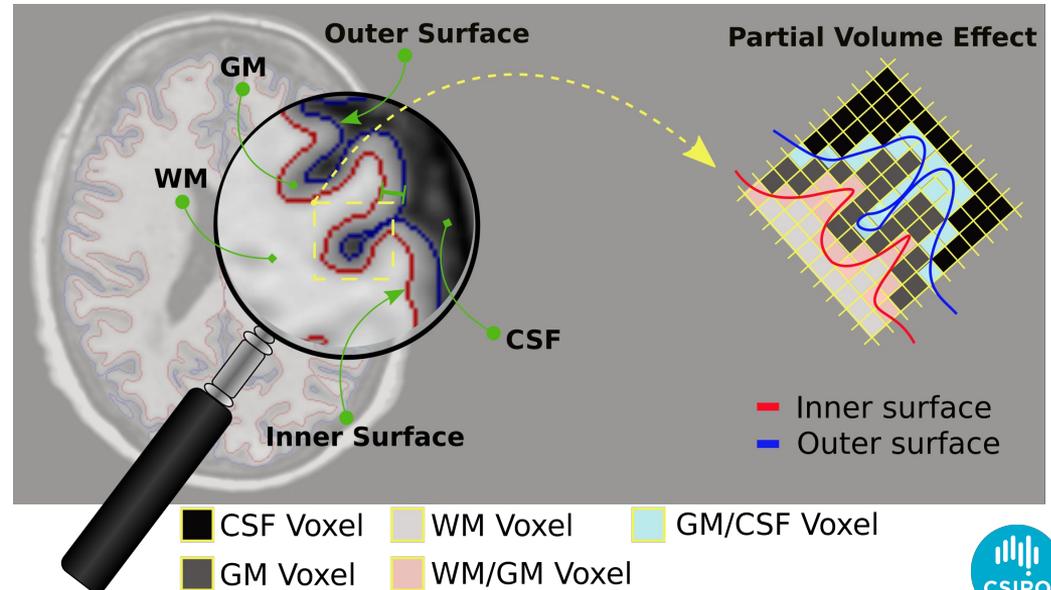
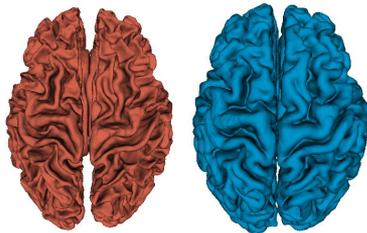


Properties:

- Connectedness ✓
- Topology ✓
- Resolution ✓

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).”

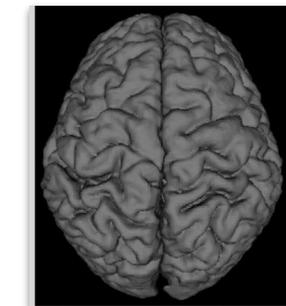
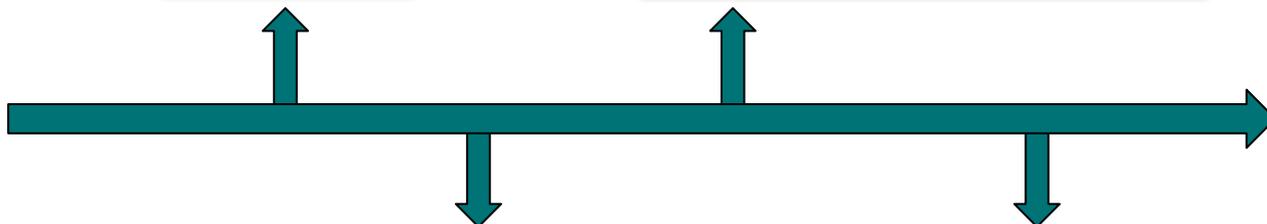
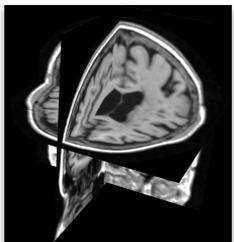
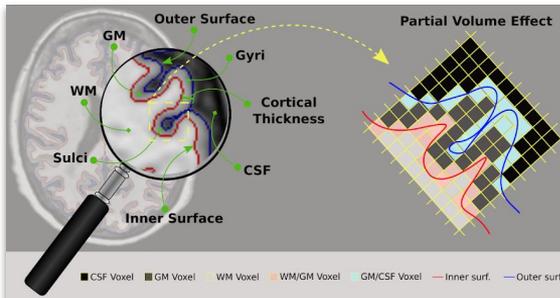


CSR Challenges

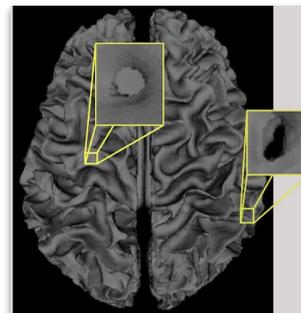
Inter-subject variability



Partial Volume Effect



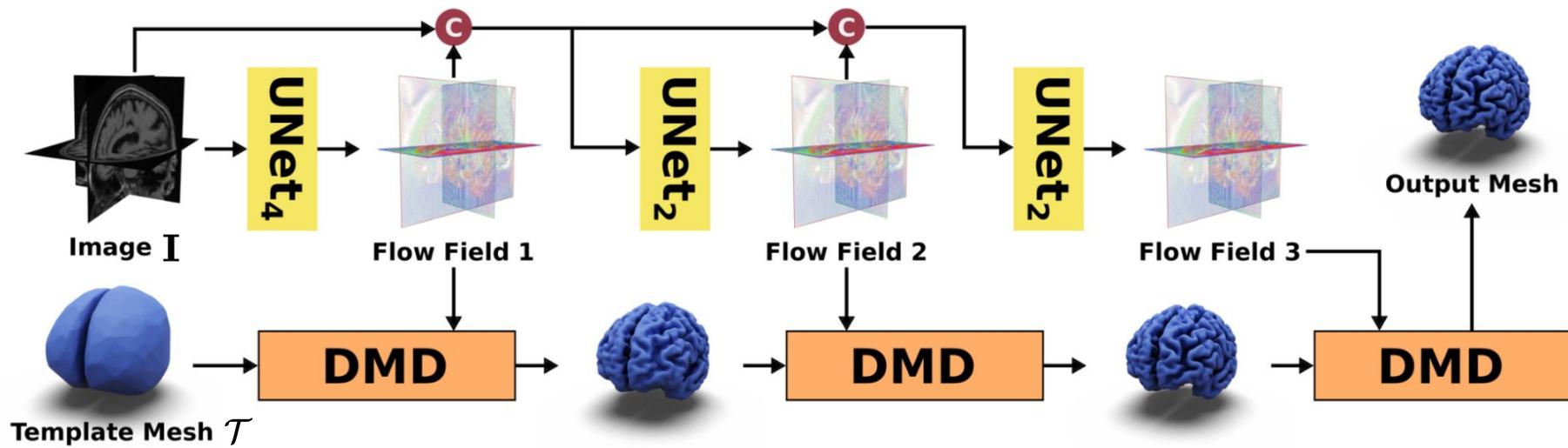
Limited MRI Resolution



Topology Defects



CorticalFlow



$$CF_{\theta_1}^1(\mathbf{I}, \mathcal{T}_1) = \text{DMD}\left(\text{UNet}_{\theta_1}^1(\mathbf{I}), \mathcal{T}_1\right)$$

$$CF_{\theta_{i+1}}^{i+1}(\mathbf{I}, \mathcal{T}_{i+1}) = \text{DMD}\left(\text{UNet}_{\theta_{i+1}}^{i+1}(\mathbf{U}_1 \hat{\cdot} \dots \hat{\cdot} \mathbf{U}_i \hat{\cdot} \mathbf{I}), CF_{\theta_i}^i(\mathbf{I}, \mathcal{T}_{i+1})\right)$$

Diffeomorphic Mesh Deformation (DMD)

Tractable framework for computing a diffeomorphic mapping Φ for each surface mesh vertex by solving the **flow ODE**,

$$\frac{d\Phi(s; \mathbf{x})}{ds} = v(\Phi(s; \mathbf{x})), \text{ with } \Phi(0; \mathbf{x}) = x$$

using the iterative approximation method,

$$V_{k+1}^i = V_k^i + hv(V_k^i), \text{ with } h = \frac{1}{N}$$

provided by the forward Euler method.

- ❖ Retains the initial mesh topology without producing self-intersections.
- ❖ We also provide sufficient and comprehensible conditions for meeting the diffeomorphic properties of these transformations.

Related work:

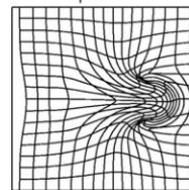
→ Scaling & Squaring in DL Registration [1]:

$$\Phi^{(1/8)} = x + v/8$$

$$\Phi^{(1/4)} = \Phi^{(1/8)} \circ \Phi^{(1/8)}$$

$$\Phi^{(1/2)} = \Phi^{(1/4)} \circ \Phi^{(1/4)}$$

$$\Phi^{(1)} = \Phi^{(1/2)} \circ \Phi^{(1/2)}$$



Voxel-wise integration
 $|I| \gg |V|$

→ Neural ODEs [2]:

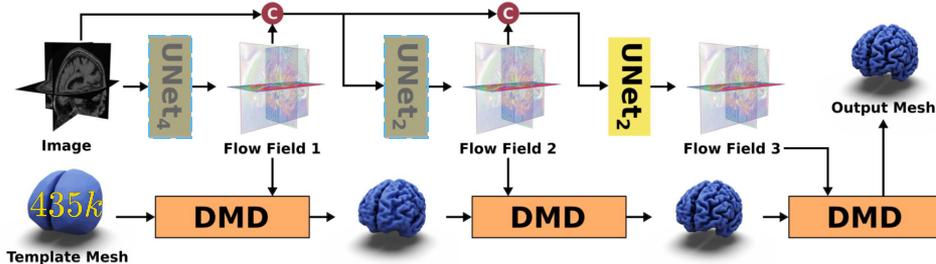
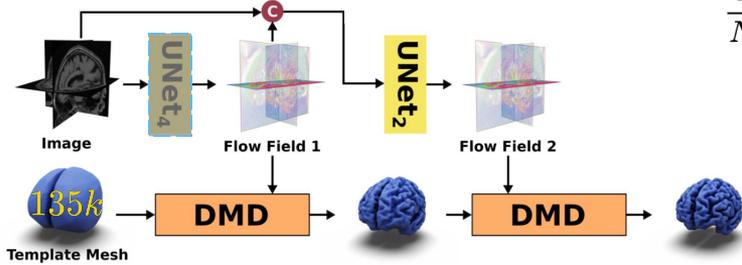
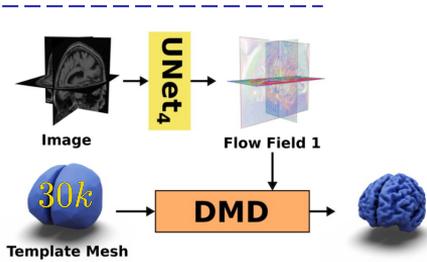
$$\Phi(x) = x + \int_0^1 f_{\theta}(x, I) dt$$

Neural Network with per
vertex image feature
extractor

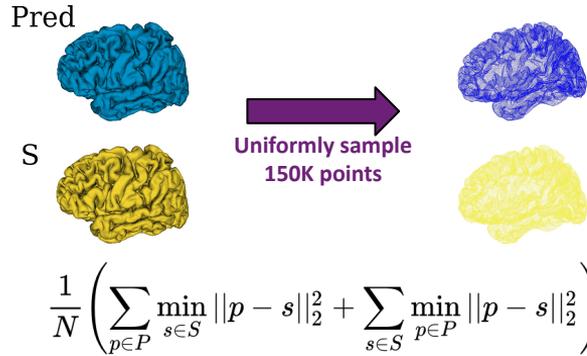
[1] - Dalca, Adrian V., et al. "Unsupervised learning of probabilistic diffeomorphic registration for images and surfaces." *Medical image analysis* 57 (2019): 226-236.

[2] - Gupta and Chandraker. "Neural mesh flow: 3d manifold mesh generation via diffeomorphic flows." *In Advances in Neural Information Processing Systems*, 2020.

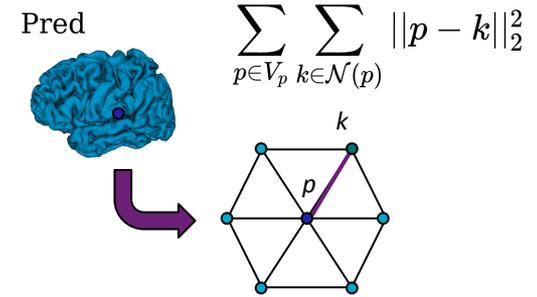
Multiscale Training



Chamfer distance:

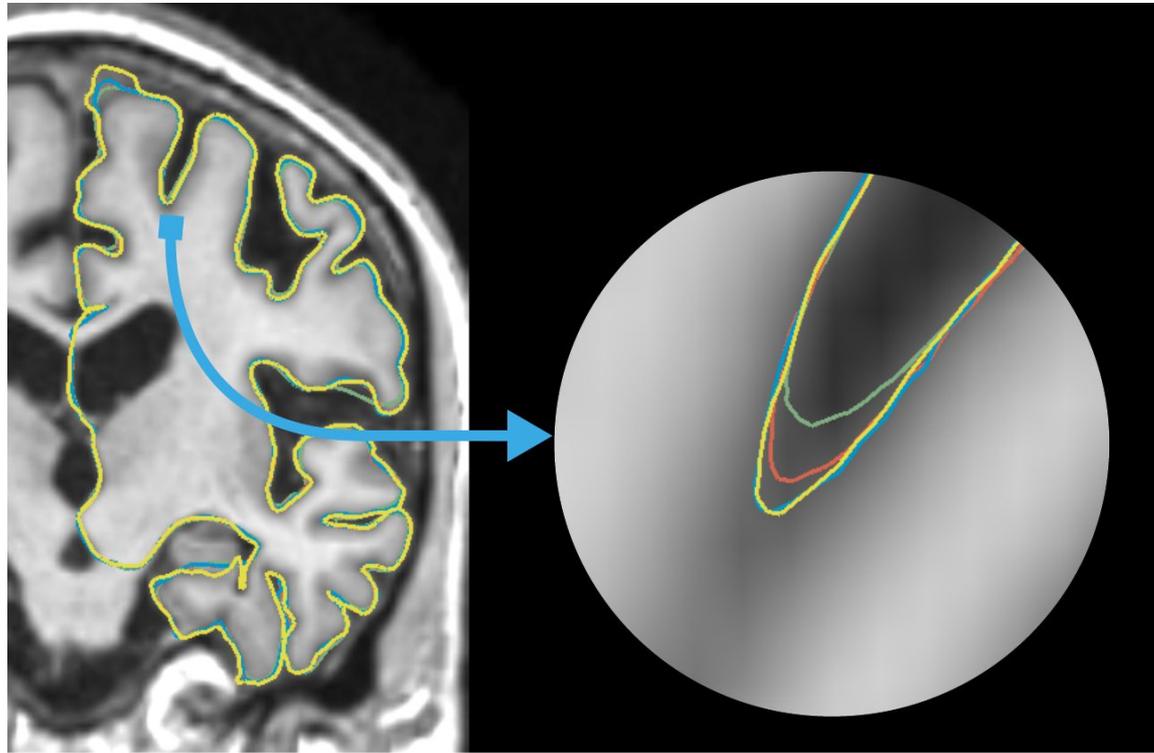


Edge length regularizer:



$$\operatorname{argmin}_{\theta_i} \sum_{(I, S) \in \mathcal{D}} \mathcal{L} \left(CF_{\theta_i}^i(I, \mathcal{T}_i), S \right)$$

CorticalFlow (CF³)



- 1st Deformation
- 2nd Deformation
- 3rd Deformation
- pseudo-ground-truth

Experiments

- **Dataset:**

- MRIs, Pseudo ground truth surfaces, and data splits proposed in [1].
- 3876 MRI images from **ADNI study**
- Pseudo ground truth surfaces generated with the **FreeSurfer V6.0 cross-sectional** pipeline.

- **Baselines:**

- **QuickNAT [2]:** Voxel-wise segmentation + surface extraction
- **Voxel2Mesh [3]:** Deformable model with regularity penalties
- **NMF* [4]:** Deformable model with diffeomorphic transformations
- **DeepCSR [1]:** Implicit surface prediction + surface extraction + Topology Correction

- **Metrics:**

- **Geometric accuracy:** Chamfer distance, Hausdorff distance, and Chamfer normals.
- **Surface regularity:** Percentage of self-intersecting faces using **PyMeshLab**.
- **Time and space complexity:** Average inference time (in seconds) and inference 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] - Roy et al. Quicknat: A fully convolutional network for quick and accurate segmentation of neuroanatomy. NeuroImage, 186:713–727, 2019.

[3] - Wickramasinghe et al. Voxel2mesh: 3d mesh model generation from volumetric data. In International Conference on Medical Image Computing and Computer-Assisted Intervention, 2020.

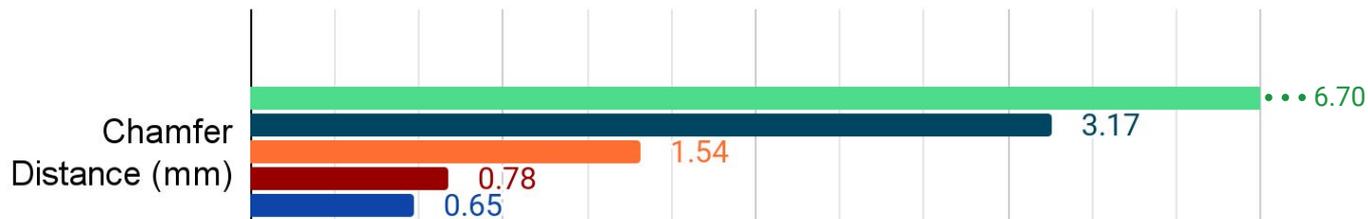
[4] - Gupta and Chandraker. Neural mesh flow: 3d manifold mesh generation via diffeomorphic flows. In Advances in Neural Information Processing Systems, 2020.



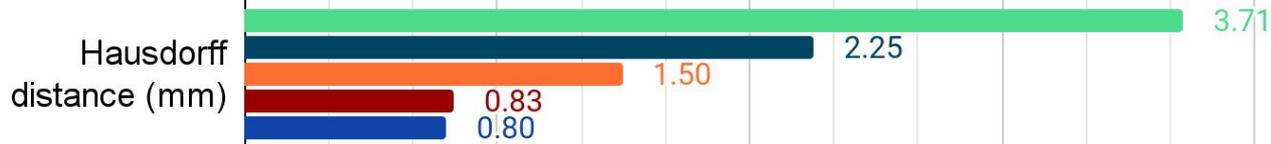
Average Geometric Accuracy

■ Voxel2Mesh ■ QuickNAT ■ NMF ■ DeepCSR ■ CorticalFlow

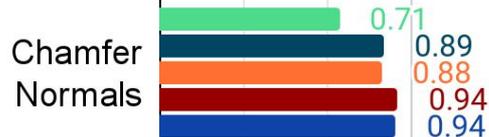
↓ Smaller
Is better



↓ Smaller
Is better



↑ Greater
Is better



0.00 1.00 2.00 3.00 4.00

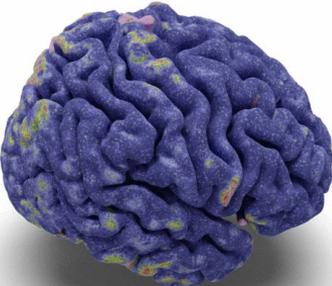
Error color coded surfaces

NMF

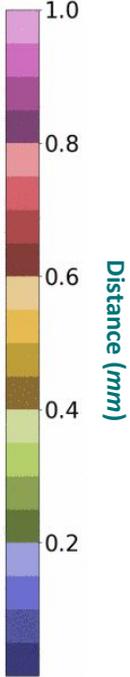
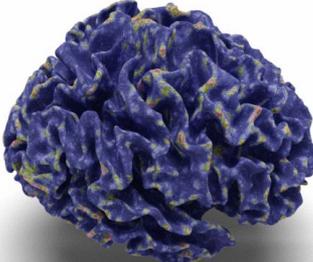
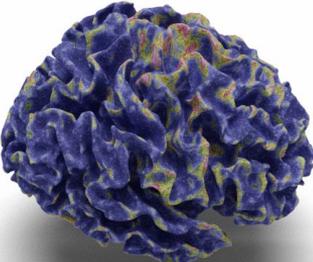
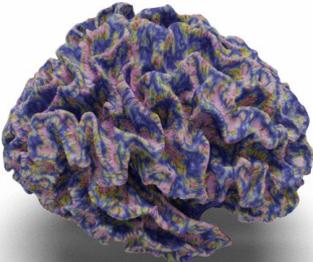
DeepCSR

CorticalFlow

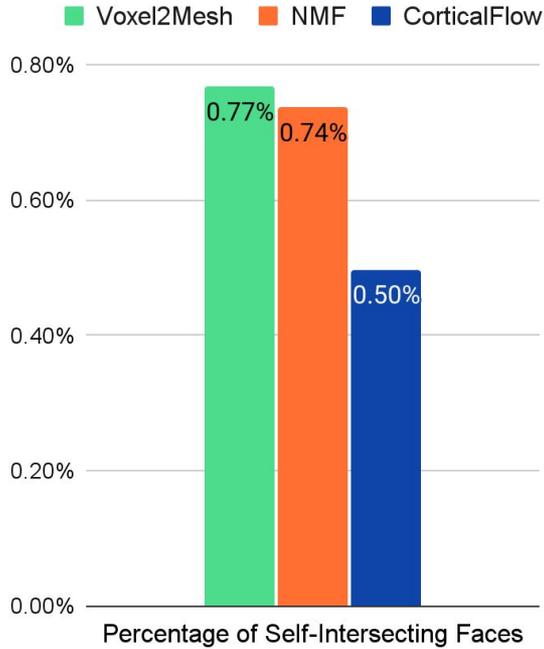
Outer Surface



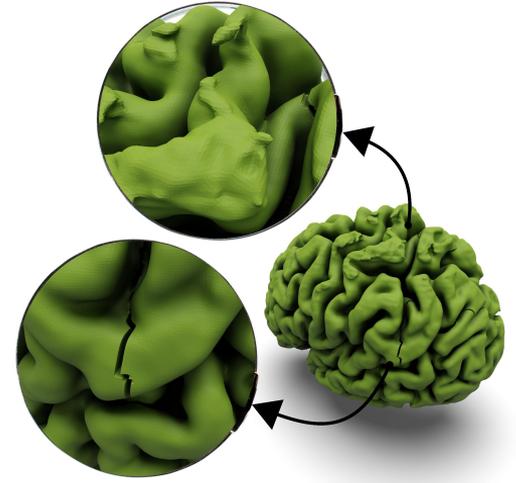
Inner Surface



Surface Regularity

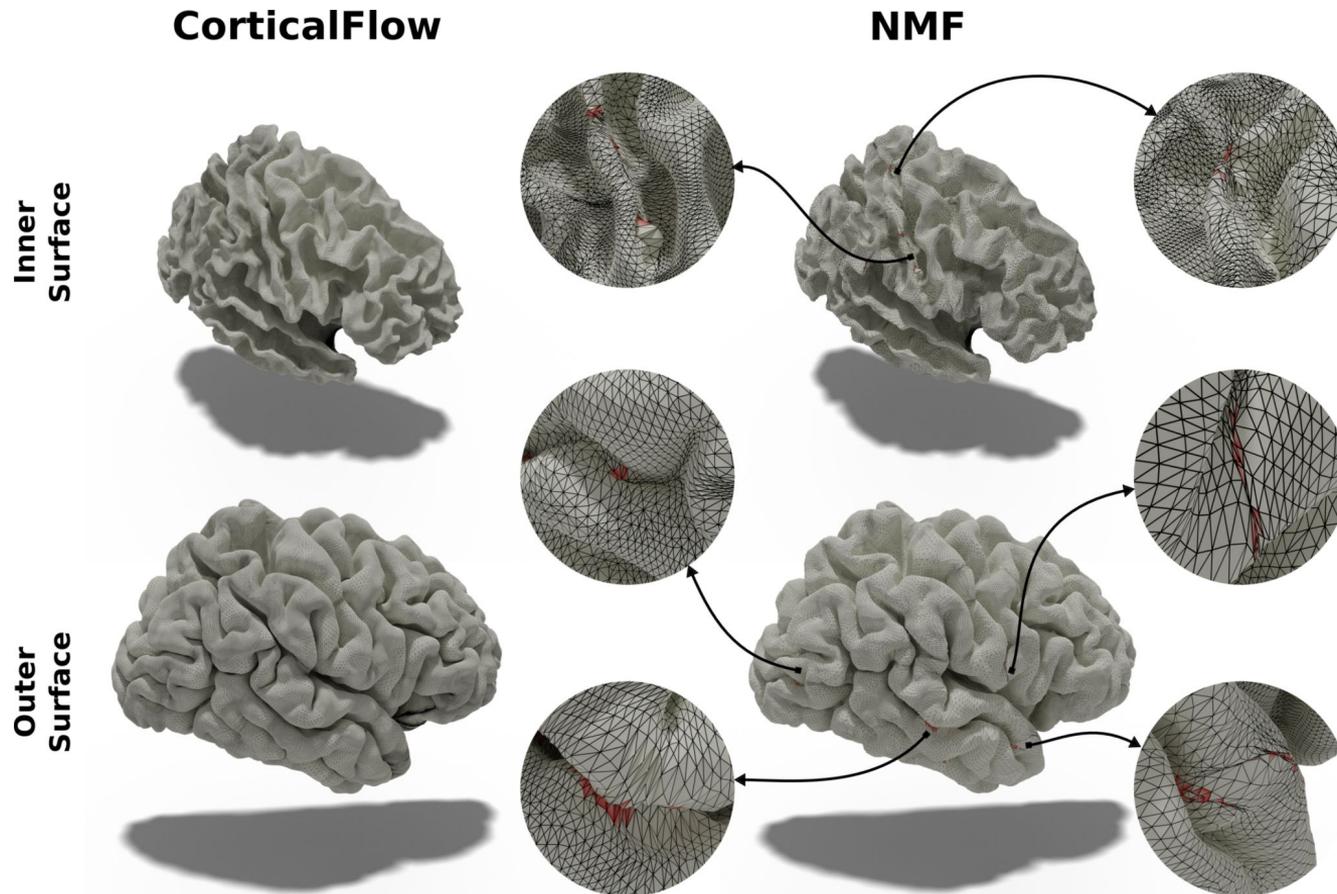


QuickNAT
Multiple connected components, handles and holes.

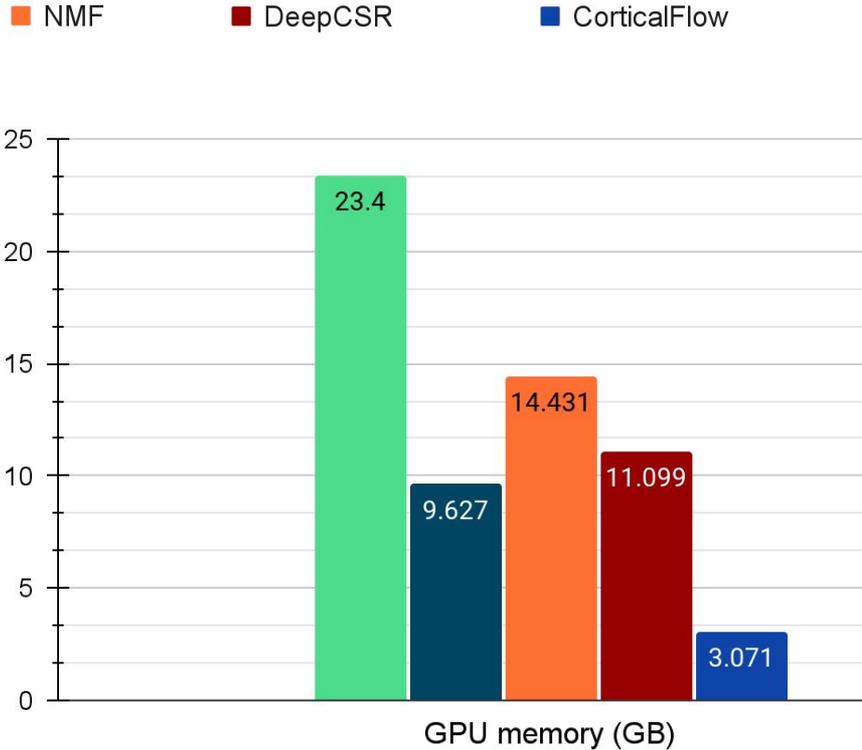
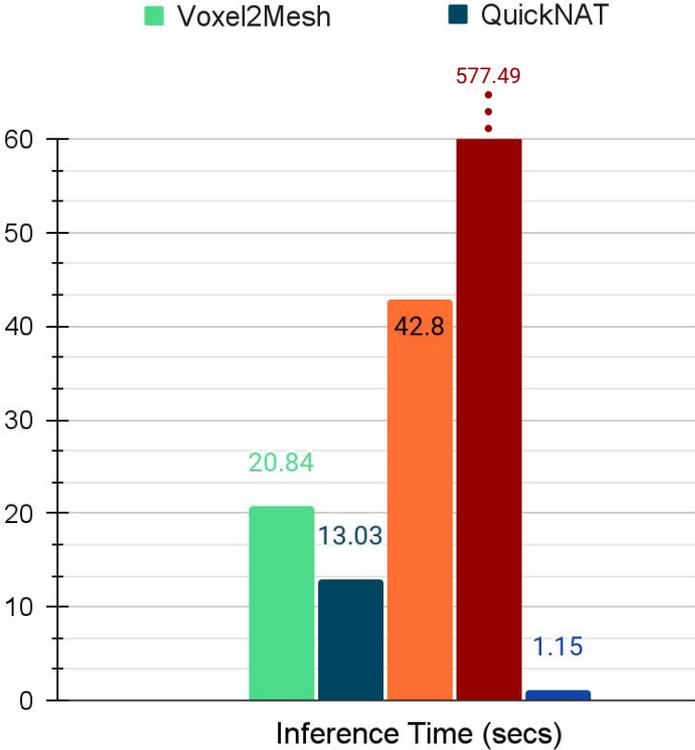


DeepCSR
Anatomical mistakes due to topology correction

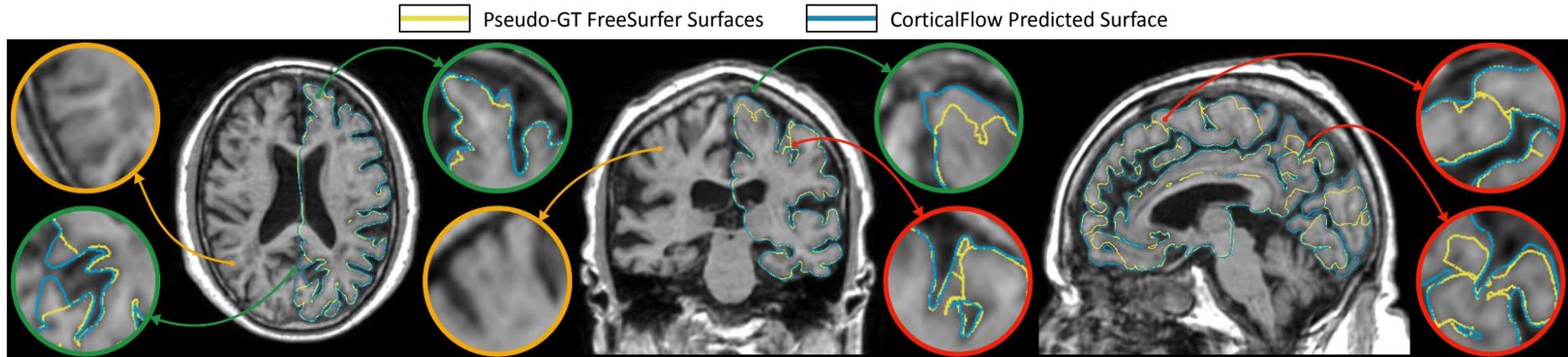
Surface Regularity



Inference Time and GPU Memory



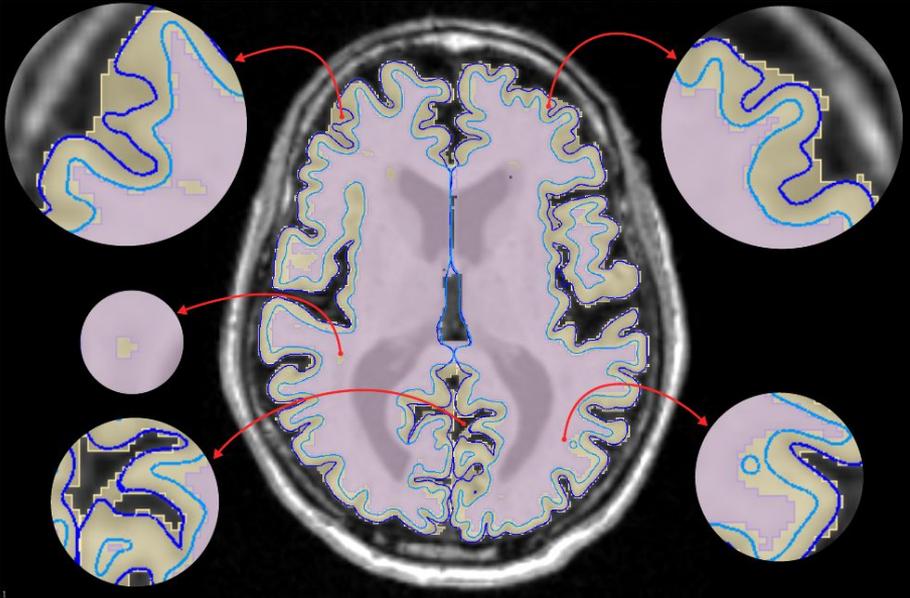
Comparison to Pseudo-Ground-Truth



- Orange circles highlight blurry MRI regions.
- Green circles highlight FreeSurfer's underestimated area.
- Red circles highlight non-plausible predictions avoided by CorticalFlow thanks to the diffeomorphism of its predicted deformations.

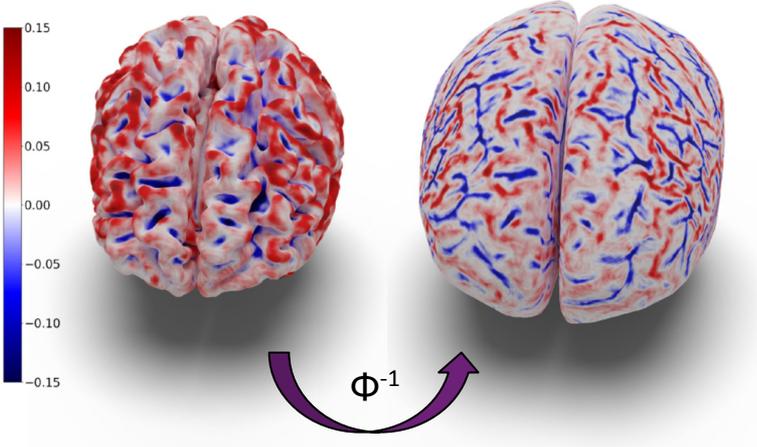
Future Applications

Segmentation at subvoxel resolution



- | | |
|--|---|
|  QuickNAT inner surface segmentation |  CorticalFlow inner surface segmentation |
|  QuickNAT outer surface segmentation |  CorticalFlow outer surface segmentation |

Analysis of surface descriptors on a common reference surface



Conclusion

This paper ...

- introduces **CorticalFlow** - a novel geometric deep learning model for efficiently reconstructing high-resolution, accurate, and regular triangular meshes from volumetric images.
- derives a **diffeomorphic mesh deformable (DMD) module** that efficiently produces diffeomorphic mappings from stationary velocity field.
- shows that CorticalFlow is more accurate, robust, faster and memory efficient than state-of-the-art models in the **cortical surface reconstruction problem** which can facilitate large-scale medical studies and support new healthcare applications.



CorticalFlow: A Diffeomorphic Mesh Transformer for Cortical Surface Reconstruction

<https://lebrat.github.io/CorticalFlow/>

