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Coupled Reconstruction of Cortical Surfaces by Diffeomorphic Mesh Deformation

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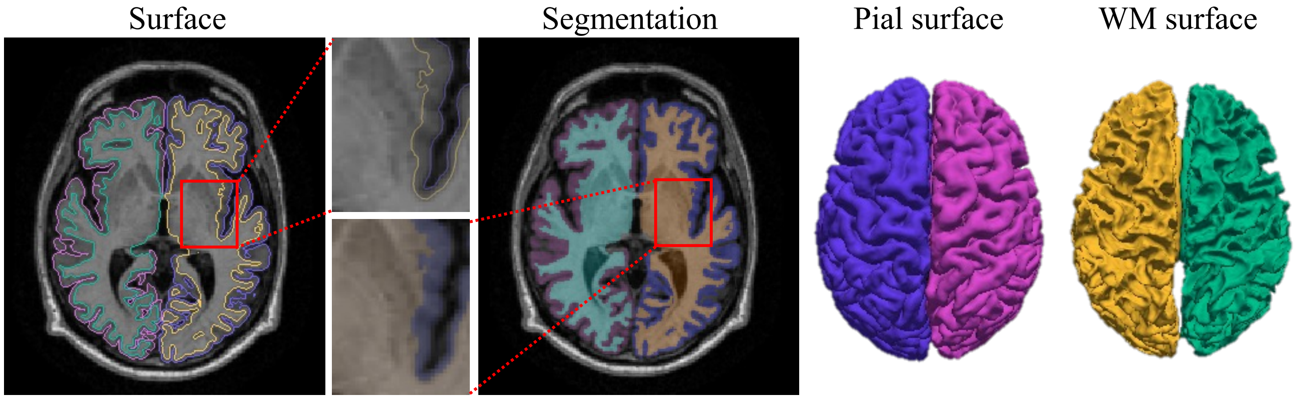
Background

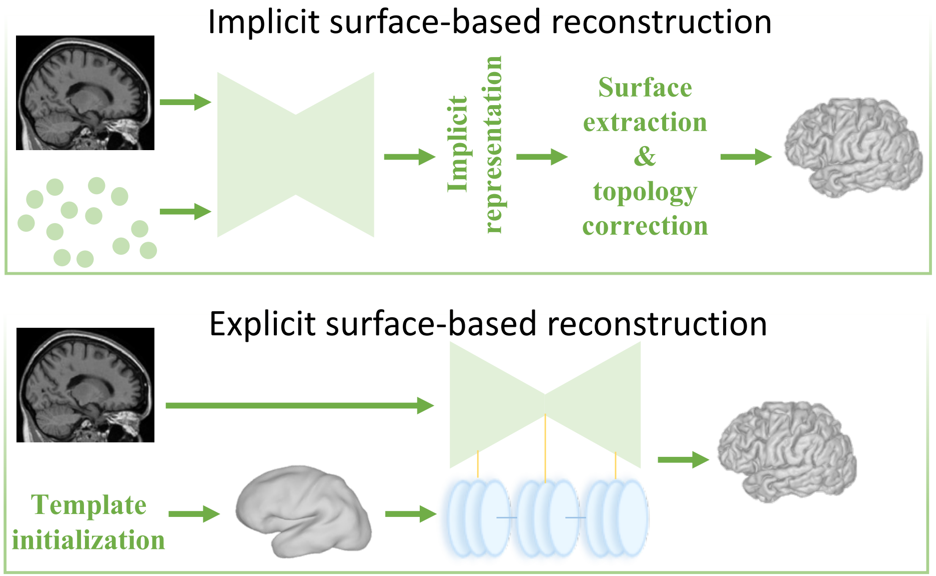
- ➢ Human cerebral cortex
  - ❑ Left/right hemispheric cerebral cortices are thin (avg. 2.5mm thickness) sheets with spherical topology
  - ❑ The cerebral cortex is highly convoluted with complex folded patterns



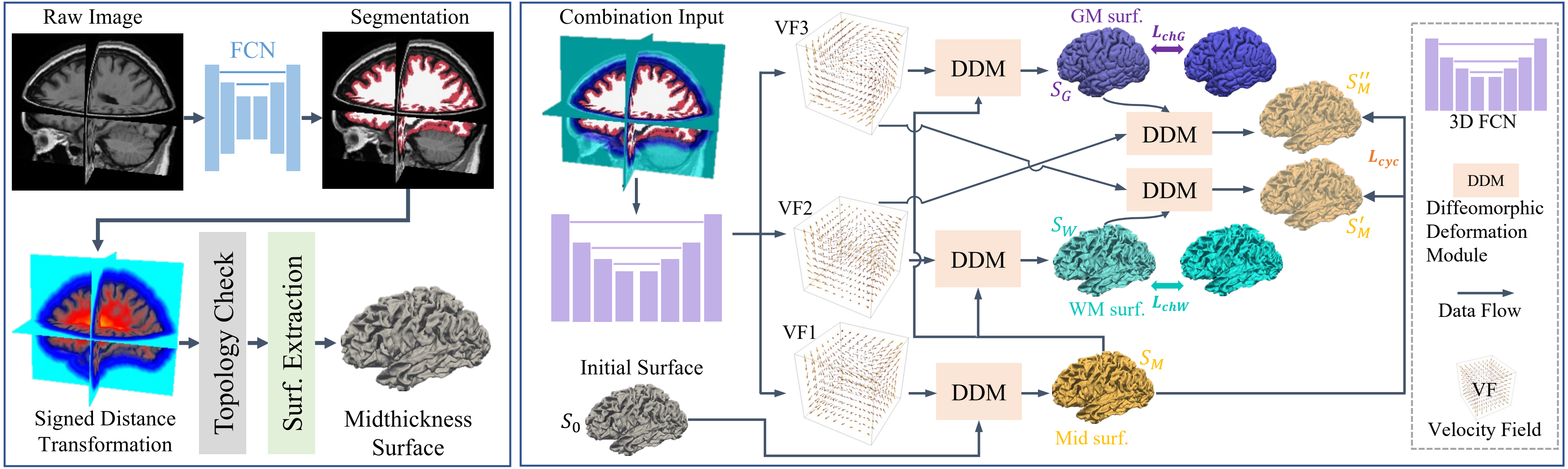
- ➢ Cortical surface reconstruction (CSR) plays an important role in surface-based analyses of the cerebral cortex

CSR Challenges

- Traditional methods
  - FreeSurfer: 6h/subject
- DL methods for CSR
  - Implicit methods
  - Explicit methods
- Limitations
  - *Interdependence* between the inner and outer surfaces is not considered
  - Complex and *parallel* DL architectures (CNN+GNN/MLP) are used
  - *Coarse* mesh template initialization makes the CSR more challenging
  - The methods are not equipped with cortical *thickness* estimation



Coupled Reconstruction of Cortical Surfaces



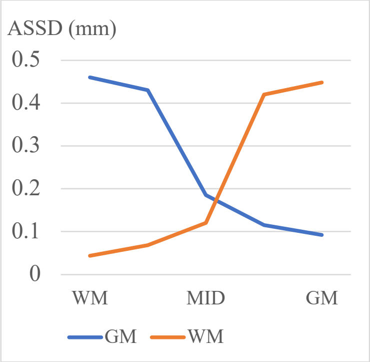
(a) Surface initialization

(b) Cortical surface reconstruction network

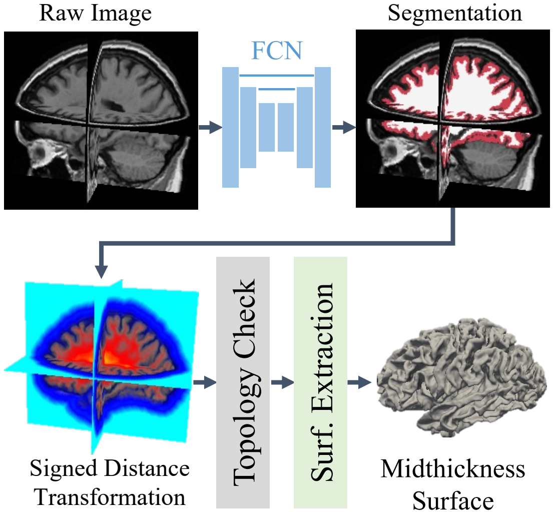
- ➢ Find a better ***initialization*** surface: midthickness surface
- ➢ Reconstruct both white matter and pial surfaces in a ***coupled*** manner

Surface Initialization

- ➢ The closer the initial surface is to its target surface, the higher the reconstruction accuracy is

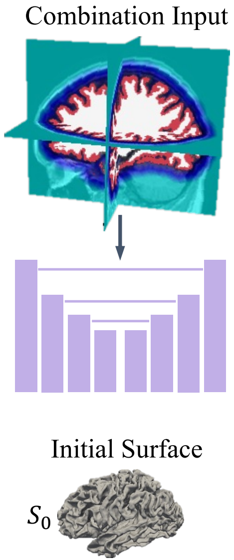


- ➢ Midthickness surface initialization
  - ❑ Generate WM/GM segmentation maps: M_W, M_G
  - ❑ Compute distance transform
    - Signed distance function (SDF): K_W, K_G
    - SDF of midthickness surface: K_M
  - ❑ Perform topology check and correction
  - ❑ Extract the initialization surface S_0 by Marching Cubes algorithm



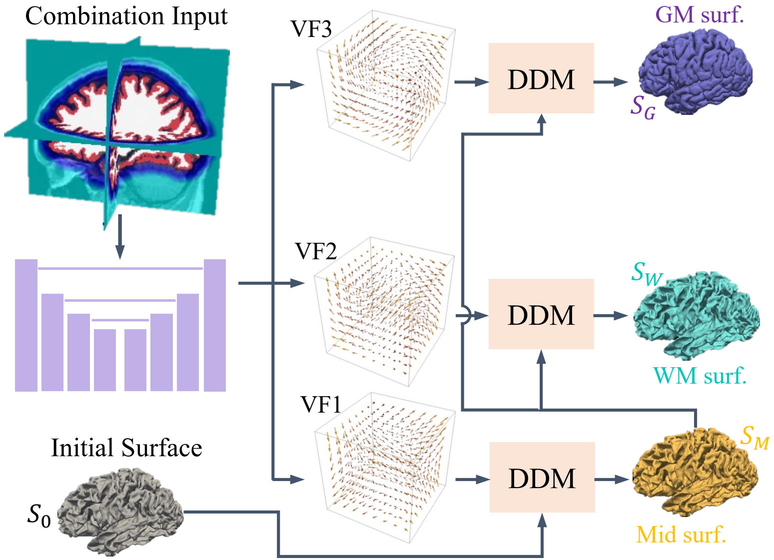
Coupled Surface Reconstruction

- Feature extraction from the input with multiple complementary information
  - **Brain MRI**: detailed texture and semantic information
  - **Ribbon segmentation maps**: structural/semantic information
  - **SDF**: surface location and relative relation between all voxel



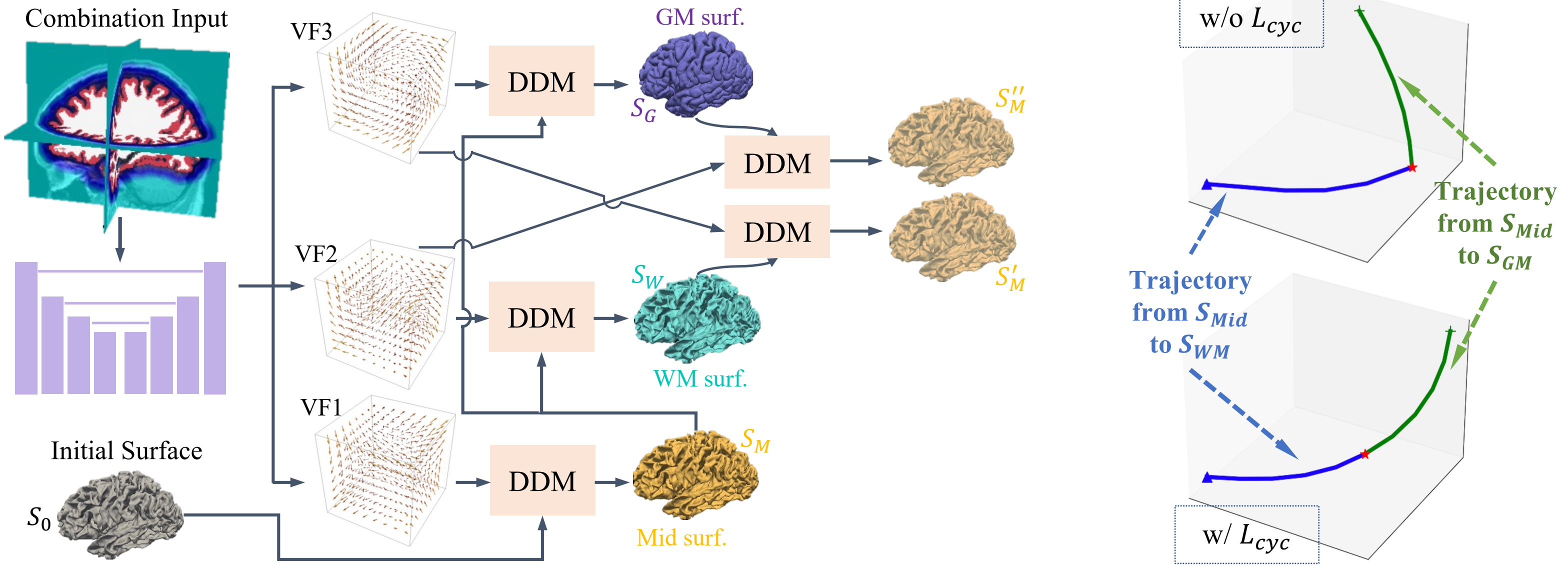
Coupled Surface Reconstruction

- Coupled Learning of Cortical Surfaces
  - GM/WM/midthickness surfaces are optimized with three diffeomorphic deformations $f_\theta(I_{comb}, S_0) = (\phi_M, \phi_W, \phi_G)$
    - $S_0 \rightarrow S_M$ $\quad$ $S_M \rightarrow S_W$ $\quad$ $S_M \rightarrow S_G$



Coupled Surface Reconstruction

- Coupled Learning of Cortical Surfaces
  - GM/WM/midthickness surfaces are optimized with three diffeomorphic deformations $f_\theta(I_{comb}, S_0) = (\phi_M, \phi_W, \phi_G)$
  - The deformations are modeled with invertible transformation: $S_M \rightarrow S_W \rightarrow S'_M$; $S_M \rightarrow S_G \rightarrow S''_M$



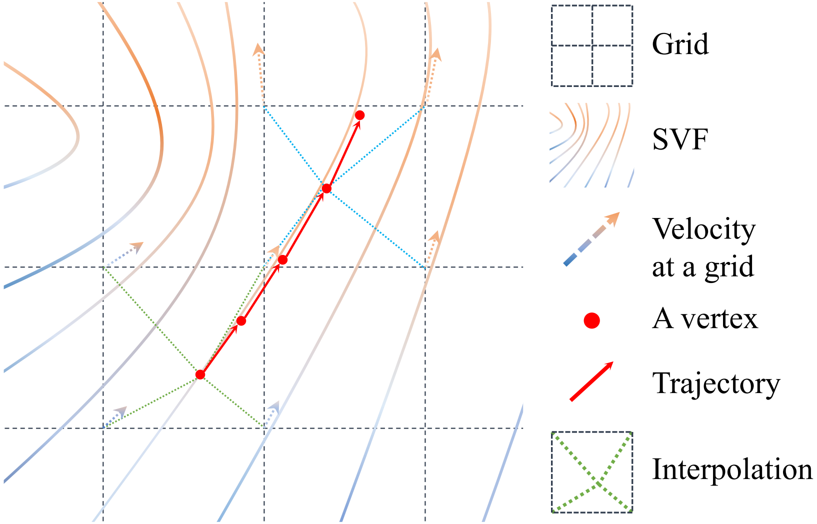
Coupled Surface Reconstruction

- Coupled Learning of Cortical Surfaces
  - Three diffeomorphic deformations $f_\theta(I_{comb}, S_0) = (\phi_M, \phi_W, \phi_G)$
  - Invertible transformation
  - Diffeomorphic deformation module (DDM)

$$\frac{d\phi(\mathbf{x},t)}{dt} = \mathbf{v}(\phi(\mathbf{x},t),t)$$

and thus $\phi(\mathbf{x},t) = \phi(\mathbf{x},0) + \int_0^t \mathbf{v}(\phi(\mathbf{x},t),t)\,dt$

- $\vec{v}_{\mathbf{x}} = Lint(\vec{v}_{N(\mathbf{x})})$
- $\vec{v}_{\mathbf{x}} \cdot \frac{1}{T}$



Loss Functions

- Mesh loss
  - Bidirectional Chamfer distance $\mathcal{L}_{chW} = \sum_{\mathbf{p} \in \mathcal{S}_W} \min_{\mathbf{p}_* \in \mathcal{S}_{W_*}} \|\mathbf{p} - \mathbf{p}_*\|_2^2 + \sum_{\mathbf{p}_* \in \mathcal{S}_{W_*}} \min_{\mathbf{p} \in \mathcal{S}_W} \|\mathbf{p}_* - \mathbf{p}\|_2^2$
- Trajectory loss
  - $S_M \to S_W; S_M \to S_G$ $\mathcal{L}_{dist} = \frac{1}{N} \sum_{\mathbf{p} \in \Omega} \|L_{Mid \to GM}(\mathbf{p}) - L_{Mid \to WM}(\mathbf{p})\|_2^2$
- Symmetric cycle loss
  - Invertibility $\mathcal{L}_{cyc} = \frac{1}{N} \sum_{\mathbf{p} \in \mathcal{S}_M} \|\mathbf{p}_{\phi_W \circ \phi_G} - \mathbf{p}\|_2^2 + \|\mathbf{p}_{\phi_G \circ \phi_W} - \mathbf{p}\|_2^2$
- Symmetric similarity loss
  - Symmetry of SVFs $\mathcal{L}_{ss} = \|\mathbf{v}_G - \overline{\mathbf{v}}_W\|_2^2$
- Normal consistency loss
  - Surface regularity $\mathcal{L}_{nc} = \sum_{e \in E, f_0 \cap f_1 = e} (1 - cos(\mathbf{n}_{f_0}, \mathbf{n}_{f_1}))$

Experiments

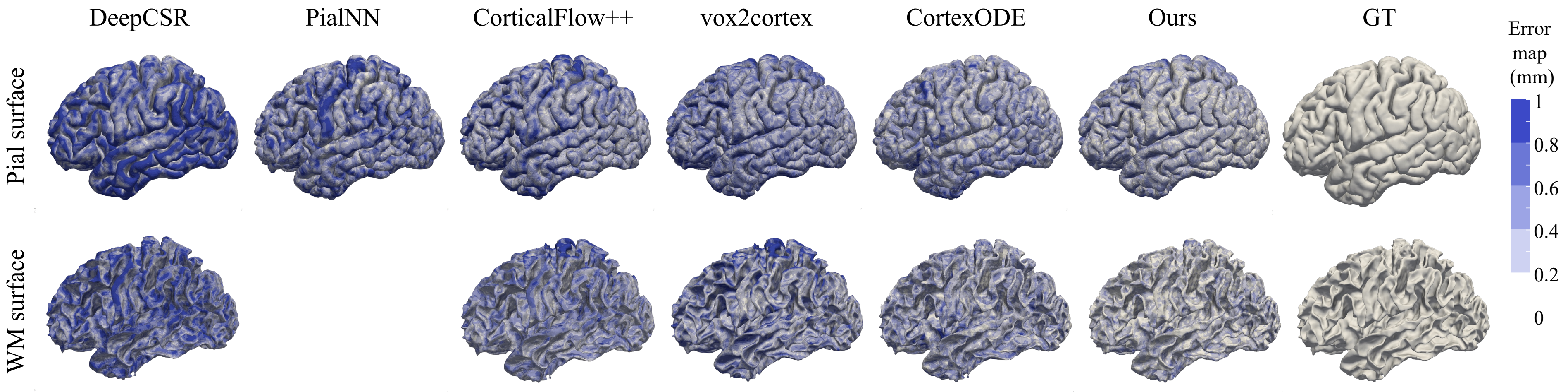
- Datasets
  - ADNI-1 dataset: 654, 50, and 113 for training, validation, and test.
  - OASIS dataset: 330, 25, and 58 for training, validation, and test.
  - Pseudo ground-truth of segmentation and surfaces generated by FreeSurfer v7.2.0.
- Baselines
  - Implicit: DeepCSR
  - Explicit: PialNN, CorticalFlow/++, cortexODE, vox2cortex
- Metrics
  - Accuracy
    - Chamfer distance (CD)
    - Average symmetric surface distance (ASSD)
    - 90^{th} percentile Hausdorff distance (HD)
  - Surface quality
    - Ratio of self-intersection faces (SIF)

Comparison with SOTA Methods

Dataset	Method	L-Pial Surface CD (mm)	L-Pial Surface ASSD (mm)	L-Pial Surface HD (mm)	L-Pial Surface SIF (%)	L-WM Surface CD (mm)	L-WM Surface ASSD (mm)	L-WM Surface HD (mm)	L-WM Surface SIF (%)
ADNI	DeepCSR [13]	0.945±0.078	0.593±0.065	1.149±0.203	\	0.938±0.076	0.587±0.064	1.137±0.193	\
ADNI	PialNN [31]	0.621±0.035	0.465±0.044	1.002±0.106	0.137±0.093	\	\	\	\
ADNI	CorticalFlow [26]	0.691±0.043	0.497±0.049	1.106±0.115	0.149±0.087	0.641±0.037	0.465±0.042	0.996±0.100	0.108±0.073
ADNI	CorticalFlow++ [47]	0.545±0.036	0.410±0.033	0.886±0.069	0.098±0.067	0.544±0.034	0.401±0.030	0.878±0.066	0.069±0.042
ADNI	cortexODE [30]	0.476±0.017	0.214±0.020	0.455±0.058	**0.022**±0.012	0.458±0.016	0.192±0.015	0.436±0.014	0.015±0.011
ADNI	Vox2Cortex [10]	0.582±0.028	0.370±0.025	0.746±0.057	0.059±0.039	0.577±0.027	0.353±0.022	0.722±0.055	0.043±0.023
ADNI	Ours	**0.410**±0.016	**0.136**±0.012	**0.293**±0.026	0.035±0.021	**0.213**±0.008	**0.071**±0.005	**0.155**±0.012	**0.007**±0.010
OASIS	DeepCSR [13]	0.986±0.085	0.617±0.070	1.331±0.212	\	0.975±0.081	0.594±0.067	1.151±0.197	\
OASIS	PialNN [31]	0.635±0.032	0.460±0.038	0.993±0.082	0.141±0.096	\	\	\	\
OASIS	CorticalFlow [26]	0.687±0.040	0.495±0.047	1.082±0.110	0.147±0.086	0.637±0.035	0.462±0.040	0.992±0.097	0.101±0.070
OASIS	CorticalFlow++ [47]	0.531±0.035	0.399±0.030	0.812±0.057	0.088±0.045	0.529±0.033	0.398±0.030	0.810±0.055	0.086±0.042
OASIS	cortexODE [30]	0.481±0.019	0.218±0.021	0.461±0.062	**0.026**±0.015	0.463±0.018	0.207±0.017	0.435±0.015	0.018±0.010
OASIS	Vox2Cortex [10]	0.588±0.032	0.381±0.030	0.750±0.063	0.061±0.037	0.581±0.028	0.375±0.027	0.731±0.059	0.046±0.027
OASIS	Ours	**0.442**±0.014	**0.161**±0.012	**0.348**±0.025	0.037±0.023	**0.218**±0.007	**0.073**±0.006	**0.159**±0.013	**0.008**±0.011

Quantitative analysis of cortical surface reconstruction on geometric accuracy and surface quality. The metrics were measured for WM and pial surfaces on two datasets. The mean value and standard deviation are reported. The best ones are in bold

Qualitative Results



Ablation Study

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➢ Input

Setting	Input			Initial mesh	L-Pial Surface			L-WM Surface		
	I	SDF	Seg	# of Lap. Sm.	CD (mm)	ASSD (mm)	HD (mm)	CD (mm)	ASSD (mm)	HD (mm)
I0	✓	✓	✓	0	0.410±0.016	0.136±0.012	0.293±0.026	0.213±0.008	0.071±0.005	0.155±0.012
I1	✓	✓		0	0.426±0.017	0.167±0.017	0.358±0.038	0.222±0.011	0.075±0.006	0.164±0.013
I2	✓				0.453±0.021	0.201±0.026	0.438±0.074	0.250±0.013	0.085±0.008	0.184±0.016
M1	✓	✓	✓	10	0.416±0.016	0.147±0.013	0.315±0.028	0.225±0.010	0.084±0.007	0.184±0.015
M2	✓	✓	✓	20	0.429±0.018	0.163±0.017	0.361±0.040	0.235±0.012	0.091±0.009	0.190±0.017

➢ Loss functions

Setting	Loss					L-Pial Surface				L-WM Surface			
	$\mathcal{L}_{CH}$	$\mathcal{L}_{dist}$	$\mathcal{L}_{cyc}$	$\mathcal{L}_{ss}$	$\mathcal{L}_{nc}$	CD (mm)	ASSD (mm)	HD (mm)	SIF (%)	CD (mm)	ASSD (mm)	HD (mm)	SIF (%)
S0	✓	✓	✓	✓	✓	0.410±0.016	0.136±0.012	0.293±0.026	0.035±0.021	0.213±0.008	0.071±0.005	0.155±0.012	0.007±0.010
S1	✓	✓	✓	✓		0.412±0.016	0.138±0.012	0.299±0.026	0.036±0.021	0.213±0.010	0.073±0.006	0.158±0.013	0.008±0.010
S2	✓	✓	✓			0.412±0.016	0.139±0.012	0.302±0.027	0.037±0.022	0.211±0.009	0.073±0.007	0.158±0.013	0.008±0.011
S3	✓	✓				0.409±0.016	0.135±0.012	0.300±0.027	0.275±0.100	0.209±0.009	0.073±0.007	0.156±0.013	0.008±0.011
S4	✓					0.404±0.015	0.129±0.011	0.278±0.024	2.522±0.791	0.203±0.009	0.069±0.006	0.153±0.013	0.009±0.012

Experimental Results

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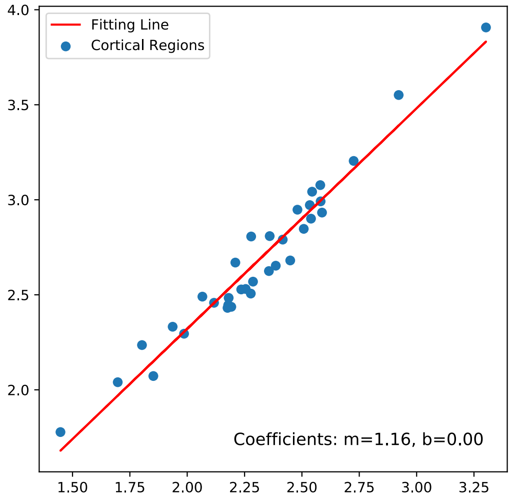
- Reproducibility
  - Datasets
    - A paired $ADNI_{1.5\&3T}$ dataset
    - Test-Retest dataset

	Method	L-WM Surface CD (mm)	ASSD (mm)	HD (mm)
ADNI-pair	Ours	**0.520**±0.053	**0.337**±0.058	**0.738**±0.151
	CortexODE	0.521±0.056	0.340±0.060	0.741±0.154
	DeepCSR	0.618±0.103	0.397±0.080	0.823±0.211
	FreeSurfer	0.556±0.049	0.364±0.054	0.764±0.118
TRT	Ours	**0.451**±0.019	**0.235**±0.030	**0.492**±0.059
	CortexODE	0.457±0.021	0.238±0.031	0.504±0.071
	DeepCSR	0.505±0.047	0.297±0.053	0.610±0.100
	FreeSurfer	0.476±0.015	0.253±0.022	0.519±0.048

- Cortical Thickness
  - ADNI-2GO
    - 100 AD & 100 normal controls
  - Compute the average cortical thickness across 35 cortical regions



Correlation between prediction (Y-axis) and GT thickness (X-axis) on 35 cortical regions (mm).

Conclusions

- A new DL framework has been developed for cortical surface reconstruction by generating a midthickness surface to initialize a **coupled reconstruction** of both the WM and pial surfaces.
- The method introduces **regularization terms** of non-negativeness of the cortical thickness and symmetric cycle-consistency of the midthickness surface's deformations to enhance the surfaces' spherical topology.
- Experiments on two large-scale neuroimage datasets have demonstrated the **superior performance** of the proposed method.
- The method generates an estimation of **cortical thickness**, facilitating statistical analyses of brain atrophy.

Thanks for your attention!

For any questions, please contact *hzheng1@upenn.edu*