FAST CORTICAL SURFACE RECONSTRUCTION AND PARCELLATION USING CURRICULUM LEARNING AND GRAPH ATTENTION NETWORKS

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ABSTRACT

Cortical surface reconstruction (CSR) and parcellation are essential processes in neuroimaging but are traditionally computationally intensive and time-consuming. While deep learning methods have enhanced efficiency, they often depend on spherical registration for individualized parcellation, adding complexity and processing overhead.

We present a novel framework that leverages Curriculum Learning and Graph Attention Networks (GATs) to achieve fast and accurate CSR and parcellation directly from structural MRI (sMRI) data. By integrating GATs into the mesh deformation pipeline, our method captures local cortical topology, enabling simultaneous reconstruction and parcellation without the need for spherical registration. This innovation reduces processing time from hours to seconds per subject while maintaining high anatomical fidelity.

Our approach demonstrates competitive performance, achieving a Dice coefficient of 0.92 for parcellation accuracy and reducing Chamfer distances to 0.752, indicating statistically significant improvements in surface reconstruction. Additionally, we introduce inter-mesh collisions between white and pial surfaces as a novel quality measure for assessing anatomical consistency.

Experiments on the Human Connectome Project (HCP) demonstrate the effectiveness of our method. An ablation study further confirms the significant benefits of our simultaneous and separate training strategies. By streamlining neuroimaging workflows, this advancement makes high-quality cortical analysis more scalable to large studies and accessible for clinical applications.

***Index Terms*—** Cortical surface reconstruction, Parcellation, Deep learning, Structural MRI, Graph neural networks

1 Introduction

CSR and parcellation are fundamental tasks in neuroimaging, enabling detailed analysis of brain structure from sMRI data [1, 2]. Traditional frameworks like *FreeSurfer* and *FastSurfer* provide reliable results but require extensive computational resources, with processing times ranging from hours to days [3]. Recent deep learning methods, such as *CortexODE* [4] and *CorticalFlow++* [5], offer improved efficiency but lack the ability to perform parcellation directly on reconstructed meshes without registration to a group template.

To address these limitations, we propose a novel architecture that integrates voxel-based methods, advanced mesh deformation, and Graph Neural Networks (GNNs) [6] for simultaneous deformation and parcellation of cortical surfaces. Our method eliminates the need for spherical registration, significantly reduces processing time, and maintains high accuracy.

Our contributions are summarized as follows:

- **Curriculum Learning for CSR and Parcellation**: We employ a sequential curriculum that leverages necessary correspondences between predicted and target vertices, enhancing learning outcomes even with approximate correspondences.
- **Innovative Neural Network Architecture**: By integrating GATs with existing CSR methods, we enable personalized deformations and parcellations, improving both accuracy and speed over *CortexODE* and *FastSurfer*.
- **New Quality Measure**: We introduce inter-mesh collisions between white and pial surfaces as a measure for evaluating cortical surface integrity.

2 Methodology

Our proposed framework, termed *CSRP* (Cortical Surface Reconstruction and Parcellation), aims to perform fast and accurate cortical surface reconstruction and parcellation directly from sMRI data. In this section, we detail the architecture and training procedures for both the deformation and parcellation components of our model.

We explore two model variations: (1) Combined Model, where deformation and parcellation are jointly trained with shared weights, and (2) Split Model, where the model is duplicated and the weights are not shared between deformation

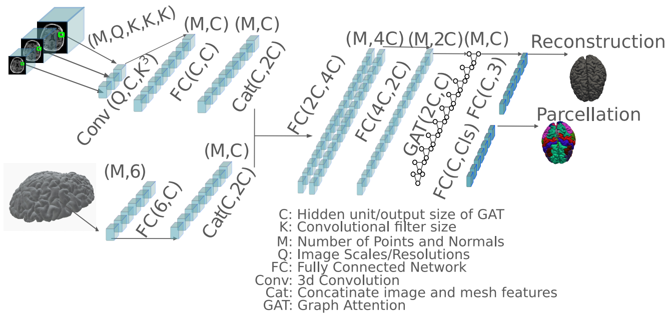

Fig. 1: Neural network architecture of our deformation and parcellation model (*CSRP*), extended from *CortexODE* [4].

and parcellation, allowing each task to specialize independently.

2.1 Deformation Pipeline

Cortical surface reconstruction involves deforming an initial mesh to align with the cortical geometry present in sMRI scans. Our deformation model builds upon the *CortexODE* architecture [4] by incorporating a GAT [6] in the final layers instead of a Multilayer Perceptron (MLP). This modification provides a receptive field along the mesh surface. The architecture of *CSRP* is illustrated in Figure 1.

We employ an Euler solver with a step size of 0.1, consistent with *CortexODE*, and utilize an 8-layer GAT. The loss functions used for training include the Chamfer loss for the predicted white matter surfaces and a combination of Mean Squared Error (MSE) loss and Chamfer loss for the pial surfaces.

During training, we extract the hemispheres of the white matter surface from the sMRI volume using a U-Net, followed by the marching cubes algorithm to generate an initial mesh. This initial mesh is then deformed towards the target white matter surface using our *CSRP* model. For training the pial surface deformation, we deform a *FreeSurfer* white matter surface into the target *FreeSurfer* pial surface.

In the inference phase, the white matter surfaces are generated in the same manner as during training. For the pial surfaces, we start with the white matter surface produced by the U-Net and marching cubes, then deform it using *CSRP* to obtain the pial surface. This process eliminates the dependency on the *FreeSurfer* white matter surface during inference.

Due to resource constraints, we trained our model for 100 epochs for the results presented in tables and 200 epochs for the figures. However, we observed that performance continued to improve up to 400 epochs, suggesting that longer training could yield even better results.

For comparison, we trained reference models—including *CortexODE*, *PialNN* [7], *TopoFit* [8], *CorticalFlow* [9], *Vox2Cortex* [10], and *CorticalFlow++* [5]—using their default training settings.

2.2 Parcellation

Cortical parcellation entails labeling regions of the cortical surface according to a predefined atlas, such as the DKTatlas40 [1]. We utilize the same *CSRP* architecture for parcellation as for deformation but focus on the final vertex positions $\mathbf{V}_f$ without backpropagating through the deformation component. The GAT outputs are fed into two independent fully connected layers: one dedicated to deformation and the other to parcellation.

We employ a two-stage curriculum learning approach for training the parcellation network, as depicted in Figure 2. In the first stage, we train *CSRP* on *FreeSurfer* surfaces, which have exact vertex correspondences and annotations from the DKTatlas40. In the second stage, we train on surfaces produced by our own deformation pipeline. Since these surfaces may not have exact vertex correspondences with the ground truth, we map the predicted vertices to the ground truth labels using a nearest neighbor KDTree [12]. In both stages, we use the Cross Entropy loss function for the classification of the DKTatlas40 classes. For combined training of deformation and parcellation, we trained the model for 100 epochs. For classification-only training, we trained for 400 epochs to ensure convergence.

2.3 Implementation Details

We processed HCP [3] sMRI data using FreeSurfer's recon-all pipeline for standard neuroimaging preprocessing, 732 training, 58 validation, and 107 test subjects, with each mesh containing approximately 130,000 vertices and 240,000 faces. Training and inference were conducted on machines equipped with NVIDIA GPUs with at least 16 GB of memory. Our models were implemented using PyTorch, PyTorch Geometric, and PyTorch3D libraries. In order to read and write *FreeSurfer* meshes and annotations we used NiBabel. We make our code available on github [1].

2.4 Mesh Quality Measures

To evaluate the performance and quality of our model, we introduce quantitative measures focused on geometric accuracy and topological correctness.

We evaluate our model using three metrics. Distance to Ground Truth is assessed by computing the Chamfer and Hausdorff distances between the predicted meshes and the ground truth meshes from *FreeSurfer*. The Chamfer distance measures the average closest-point alignment, reflecting overall surface accuracy, while the Hausdorff distance captures the maximum deviation between surfaces, indicating worst-case errors. Self-Intersection Detection identifies topological errors that compromise mesh validity by constructing a KDTree [12] of triangle centers and checking for intersecting triangles within local neighborhoods. The total number of self-intersections serves as a measure of topological and

[1]GitHub: https://github.com/neuroneural/CSRP-CSRParcellation

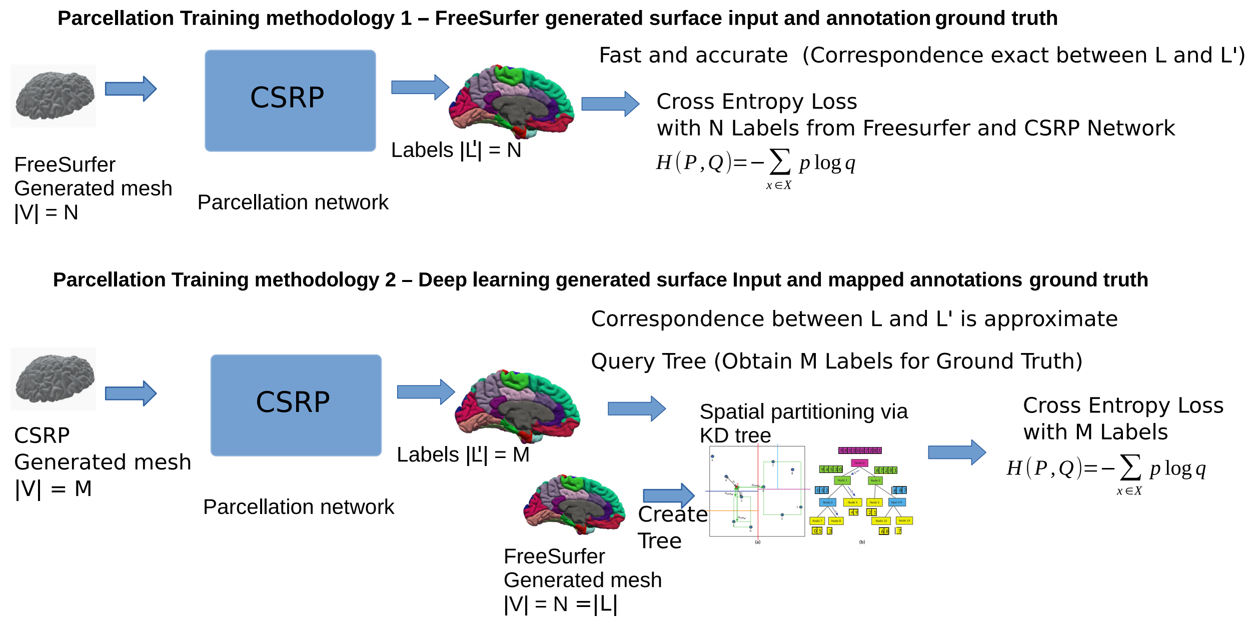

Fig. 2: Curriculum learning approach for parcellation training. We first train on *FreeSurfer* surfaces with exact vertex correspondences, then on surfaces generated by our deformation model, using nearest neighbor mapping via KDTree. KDTree illustration adapted from [11].

anatomical correctness. Lastly, Inter-Mesh Collision Assessment ensures that accurate cortical reconstructions exhibit no collisions between the white and pial surfaces, which would be anatomically incorrect. This is evaluated by checking for intersecting triangles between the two surfaces, excluding the medial wall.

3 Results

We present the performance of our *CSRP* model in cortical surface reconstruction and parcellation tasks, comparing with existing methods and highlighting improvements in accuracy and topological correctness. We also discuss findings from our ablation study on training strategies.

3.1 Improved Surface Reconstruction

Our deformation model demonstrates superior accuracy compared to *CortexODE* [4]. Table 1 presents measures including Chamfer and Hausdorff distances for gray matter (GM) and white matter (WM) surfaces.

As shown, the *CSRP (split)* model achieves a significantly lower Chamfer Distance for the white matter surface compared to *CortexODE*, indicating more accurate reconstruction. These improvements are attributed to the GAT in our deformation pipeline, effectively capturing local mesh topology.

3.2 Reduced Self-Intersections

In Table 1, we report the number of self-intersections (SIF) for each model. Our *CSRP (split)* model exhibits a higher number in the gray matter surface compared to *CortexODE*, but comparable performance in the white matter surface. We speculate that simultaneous deformation and parcellation training encourages deformations to be more *FreeSurfer*-like, reducing self-intersections. The *CSRP (combined)* model shows fewer self-intersections but at the expense of reconstruction accuracy.

3.3 Comparison of Inter-Mesh Collisions

We introduce inter-mesh collisions as a quality measure. Figure 3 shows the number of collisions for our models compared to existing methods. While our *CSRP (split)* model did not outperform *CortexODE*, it achieved better results than several other methods, indicating effective reduction of unnatural intersections.

3.4 Enhanced Parcellation Performance

We evaluate parcellation performance using the Macro Dice coefficient. Table 2 presents the scores for gray matter (GM) and white matter (WM) surfaces. Our *CSRP (class only) + FrS* model, which uses *FreeSurfer* surfaces and trains only the parcellation network, achieves the highest Macro Dice score for the gray matter surface, outperforming *FastSurfer* [2]. The superior performance of the *CSRP (class only) + FrS* model suggests that achieving ideal parcellation requires surfaces close to the ground truth. This highlights the importance of accurate surface reconstruction. Figure 4 displays example parcellated surfaces predicted by our method, *FastSurfer*, and *FreeSurfer*. Our method produces high-quality parcellations that closely match the ground truth. We speculate that self-intersections may adversely affect parcellation performance,

Table 1: Comparison of surface reconstruction measures for different models. An independent samples t-test revealed that the *CSRP (split)* model shows a significant improvement over *CortexODE* in Chamfer Distance for the white matter surface ($p < 0.0001$) with n = 107 subjects.

Model	Chamfer Distance (mm)		Hausdorff Distance (mm)		Self-Intersections (SIF)	
	GM	WM	GM	WM	GM	WM
CSRP (split)	0.916 ± 0.027	**0.752 ± 0.014**	5.784 ± 1.372	**4.958 ± 1.355**	9620.23 ± 2802.54	80.17 ± 103.36
CSRP (combined)	1.041 ± 0.033	0.914 ± 0.015	5.858 ± 1.332	5.199 ± 1.386	3602.79 ± 1162.76	8.96 ± 23.36
CortexODE	**0.890 ± 0.026**	0.766 ± 0.014	**5.692 ± 1.316**	4.985 ± 1.371	**822.69 ± 426.50**	**1.50 ± 3.50**

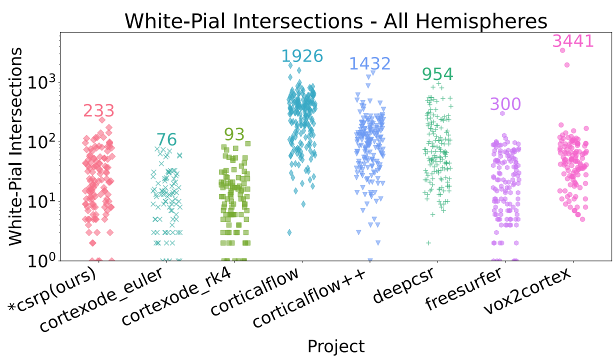

Fig. 3: Inter-mesh collisions between white and pial surfaces. Lower values indicate fewer collisions and better anatomical consistency. Our *CSRP (split)* model outperforms several existing methods, though not *CortexODE*.

Table 2: Macro Dice Scores for Parcellation Performance. An independent samples t-test revealed that the *CSRP (class only) + FrS* model significantly outperforms *FastSurfer* in the gray matter surface ($p < 0.0001$) with n = 107 subjects.

Model	Macro Dice (GM)	Macro Dice (WM)
CSRP (split)	0.8716 ± 0.0181	0.9142 ± 0.0175
CSRP (combined)	0.8630 ± 0.0206	0.9143 ± 0.0170
CSRP (class only) + FrS	**0.9193 ± 0.0168**	0.9236 ± 0.0165
FastSurfer	0.8729 ± 0.0154	**0.9277 ± 0.0140**

as they can cause perforations between gyri, making accurate classification challenging.

3.5 Ablation Study: Training Strategies

Our ablation study assesses the impact of simultaneous versus separate training of deformation and parcellation networks. The *CSRP (split)* model, where tasks are trained separately, generally outperforms the *CSRP (combined)* model in reconstruction accuracy. However, combined training reduces self-intersections, suggesting that multitask learning provides a mechanism to address this challenge.

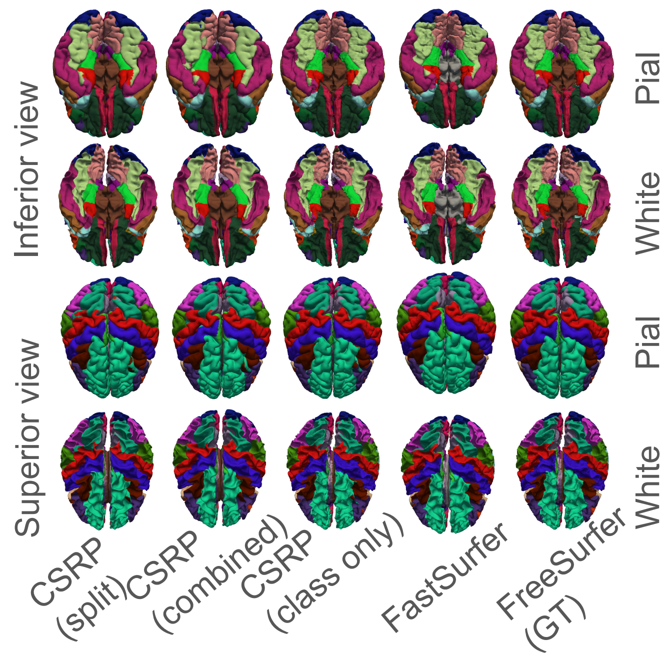

Fig. 4: Example parcellated surfaces predicted by *FastSurfer*, our method (*CSRP*), and *FreeSurfer*. Our method shows improved accuracy in certain regions compared to *FastSurfer* in our class only version, which requires surfaces very close to the ground truth.

4 Conclusion

We have presented a novel *CSRP* model that incorporates a GAT and a curriculum learning approach to improve cortical surface reconstruction and parcellation. Our method effectively captures local mesh topology and leverages task-specific training, outperforming existing methods in key measures while significantly reducing processing time. The ablation study highlights the benefits of both simultaneous and separate training. Future work will focus on reducing topological errors and refining the balance between accuracy and topological correctness to further enhance performance.

5 Compliance with Ethical Standards

This research study was conducted retrospectively using human subject data made available in open access by the Human Connectome Project [3]. Ethical approval was not required as confirmed by the license attached with the open access data.

6 Acknowledgments

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