Supplemental Material

1. DIFFERENCES FROM PREVIOUS DIFFEOMORPHIC TRANSFORMATION-BASED CORTICAL SURFACE RECONSTRUCTION METHODS

Diffeomorphic transformation-based cortical surface reconstruction [1–5] typically models smooth deformation from an initial triangular mesh to another using an ODE. This process generally describes the reconstruction of either the inner white matter surface, the outer pial surface, or both concurrently. Theoretically, they are defined as follows:

$$\frac{\partial}{\partial t}\phi_t = v(\phi_t, \boldsymbol{I}),\ \phi_0 = S_0, \tag{S1}$$

$$\phi_T = S_0 + \int_0^T FC(\phi_t, F_2)\mathrm{d}s. \tag{S2}$$

Taking the template to white matter surface as an example, S_0 represents the initial smooth surface, $\boldsymbol{I}$ denotes the input brain MRI and ϕ_T denotes the reconstructed surface. Typically, given the initial condition S_0, the final surface ϕ_T is obtained using numerical solutions of differential equations, such as Euler or Runge-Kutta method. During this solution process from $[0, T]$, a series of byproducts are generated within $(0, T)$. These intermediate state surfaces lack practical significance, implying that the deformation process lacks interpretability.

For the proposed ACDE, rather than modeling an uninterpretable deformation process, it is designed to model the developmental trajectory at the population level. When a specific brain MRI is provided as condition, the ACDE adapts to model the individual-level developmental trajectory. Fig. S1. illustrates the differences between the proposed method and other diffeomorphic transformation-based cortical surface reconstructions. Our method offers an interpretable process, imbuing the reconstruction with developmental significance. Furthermore, it enables simultaneous reconstruction of the cortical surface corresponding to the brain MRI and establishment of its prior developmental trajectory in a single solution process, whereas previous methods only yield the reconstructed surface without interpretability in the iterative process.

2. DIFFERENCES FROM PREVIOUS DEVELOPMENTAL PREDICTION METHODS

Previous methods capable of developmental prediction were predominantly based on morphological features extracted from cortical surfaces via neuroimaging pipelines like Freesurfer [6–8]. To mitigate the influence of the cortex's complex morphology, these features are typically mapped onto a standard spherical space for subsequent analyses. Spherical UNet and its variants [9–11] are commonly employed for longitudinal prediction. However, most of these architectures are trained at predefined fixed time points, and a single model can only map one time point to another. This design requires substantial paired data at each time point, often challenging to obtain in clinical settings. To address this issue, DITSAA [11] was introduced to achieve cortical prediction at multiple time points based on irregularly collected dataset. The DITSAA first disentangles age from input cortical features, then integrates the desired age segment information, ultimately enabling developmental prediction at any time point. This method models brain development on sparse longitudinal data across multiple time points, such as datasets where each subject's scans cover only two time points but collectively span the desired 0–24 month range of infant brain development. Although DITSAA establishes a more flexible model, it still requires paired data for training. Clinically, the volume of data at single time points far exceeds that of research-specific longitudinal data. Thus, how to effectively use both single and multiple time point data to construct developmental trajectories remains an area requiring further attention.

The proposed method is based on diffeomorphic transformation-based cortical surface reconstruction, directly constructing developmental trajectories at the surface level. This approach captures more information, particularly reflecting the substantial age-related changes in the cortical folding pattern during early neonatal or fetal development. Single cortical features struggle to represent such drastic changes, constraining longitudinal analysis. Moreover, proposed method effectively utilize unpaired data for precise longitude generation. Finally, our method generates

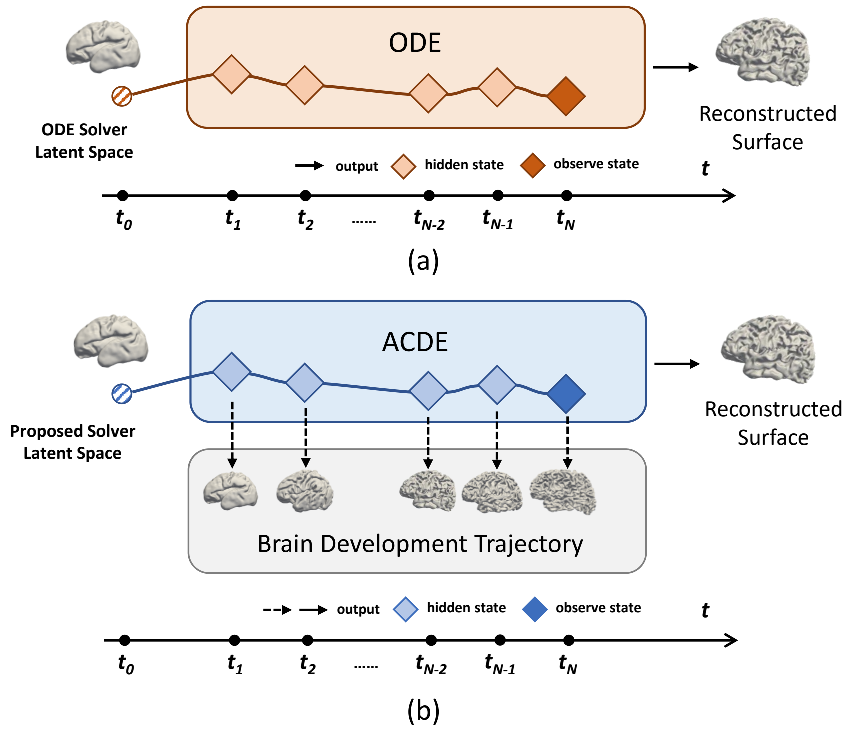

Fig. S1. Differences from Previous Diffeomorphic Transformation-Based Cortical Surface Reconstruction Methods. (a) Standard Solution. (b) Proposed method.

cortical surfaces for multiple time points in a single iteration, in contrast to Spherical UNet and its variants, which generate only one cortical feature per inference. These characteristics demonstrate the superiority and flexibility of our approach.

3. VISUALIZATION RESULTS

In this section, additional visualization results of the generated brain development trajectory are presented (below the references).

REFERENCES

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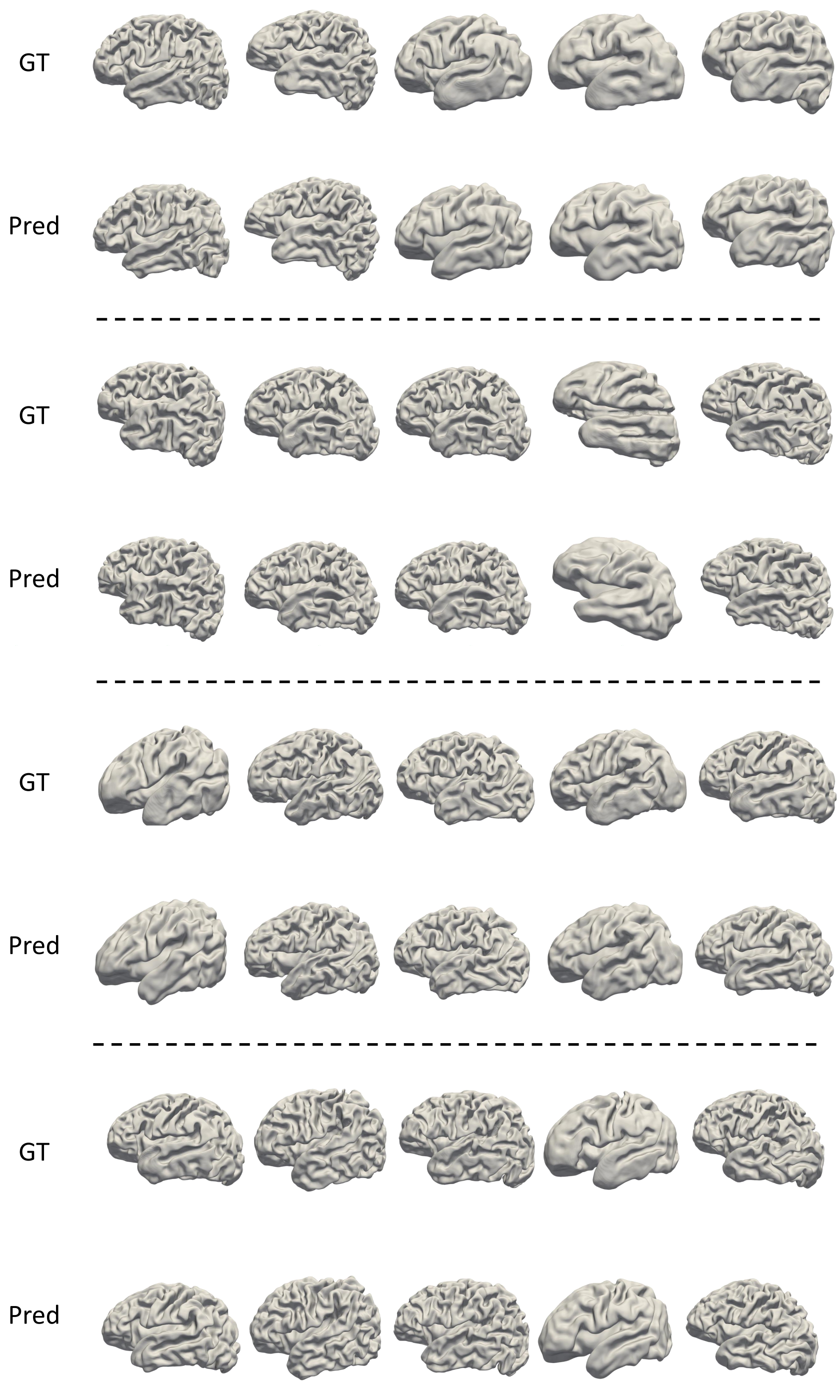

Fig. S2. Visualization of white matter surfaces. GT: Ground Truth surfaces. Pred: Predicted Surfaces.

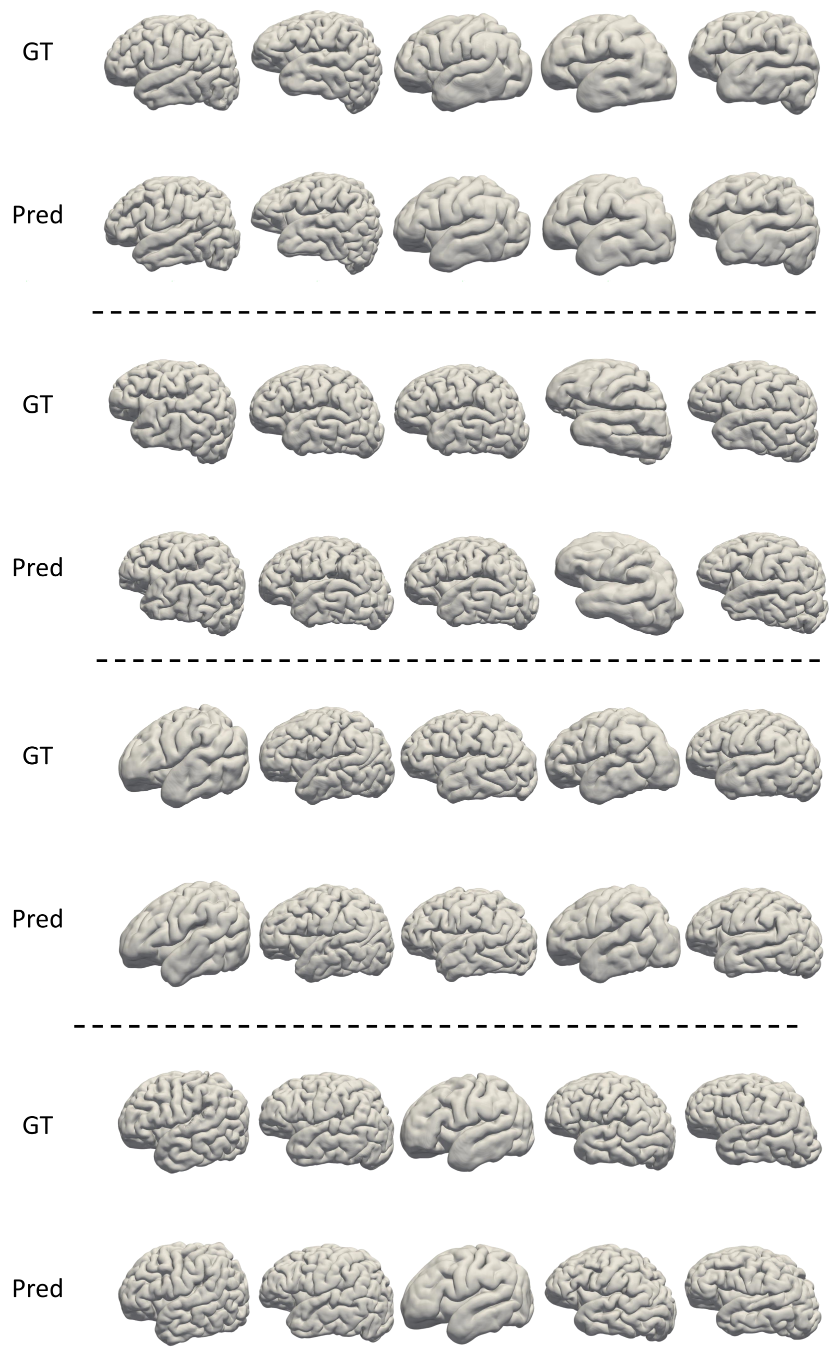

Fig. S3. Visualization of pial surfaces. GT: Ground Truth surfaces. Pred: Predicted Surfaces.