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## UNSUPERVISED CORTICAL SURFACE REGISTRATION NETWORK FOR ALIGNING GYRALNET

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### Abstract

The cortical 3-hinge gyrus (3HG) and its network (GyralNet) play key roles in understanding the regularity and variability of brain structure and function. However, existing cortical surface registration methods overlook these features, resulting in suboptimal alignment across subjects. Currently, no 3HG and GyralNet atlas exist for registration, and generation of the corresponding atlas requires extensive runtime using traditional methods. To enable better registration of these features, we introduce an unsupervised learning framework to jointly develop 3HGs and GyralNet atlas and register the individual cortical features onto the atlas. To incorporate the graph structure of 3HGs and GyralNet into the registration network, we convert them into surface distance maps, facilitating effective integration. To effectively learn large deformations, a multi-level spherical registration network based on spherical U-Net is introduced to perform registration in a coarse-to-fine manner. Experiments demonstrate our approach's ability to generate 3HGs and GyralNet atlas with detailed patterns and effectively improve registration accuracy.

### Index Terms—

3-Hinge Gyrus; GyralNet; Cortical Surface Registration; Spherical U-net

## 1. INTRODUCTION

Recently, a unique cortical folding structure known as the 3-hinge gyrus (3HG) and its associated network (GyralNet) has been identified. A 3HG is defined as the convergence

### COMPLIANCE WITH ETHICAL STANDARDS

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

point of gyri from three distinct directions [1]. This structure, distributed across the entire cerebral cortex, is distinguished by its notably thick cortex and dense long-range fibers compared to other gyral or sulcal regions [2]. Research suggests that 3HGs serve dual roles, participating in both broader functional networks during resting state and localized networks during specific tasks [3,4]. The structural and functional importance of 3HGs underscores their role as critical hubs in brain networks, offering a promising avenue to investigate the complex brain connectivity [5,6]. Consequently, establishing precise cross-subject correspondences for 3HGs and constructing 3HG-centered brain networks at a finer scale can significantly advance our understanding of the brain network organization. However, since 3HGs are identified on each individual cortical surface, they demonstrate substantial individual variabilities and pose a significant challenge for existing methods to align them [7,8]. Thus, a model that can efficiently and effectively align 3HGs is highly desirable. Meanwhile, successful 3HGs alignment could serve as a key benchmark for assessing the accuracy of cortical registration.

Existing cortical surface registration methods [9,10] have three primary limitations. 1) They rely on cortical geometric features to guide deformation, overlooking high-level structures such as 3HGs and GyrNet, which leads to suboptimal alignment of cortical structural features. 2) The GyrNet represents the cortical folding pattern as a graph composed of nodes and edges that converge at joints representing various gyral crests, making it incompatible with conventional registration methods. 3) Conventional methods typically require multiple rounds of atlas estimation and individual-to-atlas registration, requiring extensive runtimes when averaging cortical features like 3HGs and GyrNet when atlas is not available [11–15].

To address these limitations, we propose an unsupervised learning framework that simultaneously develops a cortical surface atlas of 3HGs and GyrNet and predicts the deformation field between the atlas and individual cortical surface. It achieves great efficiency compared to conventional methods by jointly generating the atlas and registering cortical features. Recognizing that 3HGs and GyrNet are represented as nodes and graphs, we introduce a novel strategy to convert them into continuous distance maps on the spherical surface, enabling them to be integrated into the registration network and thus improving the accuracy for aligning individual cortical features to corresponding atlases. To effectively extract features from these distance maps generated from 3HGs and GyrNet, we use the spherical convolution [16] to build our atlas synthesis and unsupervised registration network, which has demonstrated significant capability in describing the local spatial patterns on the spherical surface [17]. Given the challenges of learning large deformations [18], we introduce a deep multi-level spherical registration network (ML-S3Reg) [19] that breaks down large deformations into smaller deformations at each resolution level, performing cortical surface registration in a coarse-to-fine manner. Extensive experiments on the Human Connectome Project dataset demonstrate that 3HGs and GyrNet atlas generated with our proposed framework exhibit more detailed patterns and achieve better registration accuracy.

## 2. METHOD

To better align 3-hinge gyri across subjects and generate a high-resolution atlas for 3HG and GyralNet, we propose a unified framework consisting of an atlas synthesis network and a registration network, which is elaborated below.

### 2.1. Distance Map Generation

To improve the registration accuracy of cortical structural features, especially the gyral crests, we aim to incorporate the GyralNet features into our framework. The 3HGs are represented as nodes defining the convergence point of gyri from three distinct directions, while the GyralNet is the set of curves connecting the 3HGs. This graph-like structure differs from the conventional cortical morphological features, such as average convexity and mean curvature, rendering the current registration methods inapplicable. Therefore, we propose to convert the GyralNet and 3HGs into distance maps on the spherical cortical surface, as shown in Fig. 1, to enable compatibility with cortical morphological features and facilitate seamless integration. The distance is defined as the geodesic distance from each cortical surface vertex to its nearest 3HG or GyralNet point. These distance maps provide spatially continuous patterns characterizing the shape of gyral crests, thereby guiding the network to better align the 3HGs and GyralNet.

### 2.2. Network Architecture

As shown in Fig. 2, our method aims to jointly learn a generative model  $G_t$  that can synthesize an atlas  $A_t$  given on-demand attributes, e.g., the age  $t$  of an input scan, and a registration model that registers the synthesized atlas to each input surface, thus avoiding the expensive computational cost of the multi-round group-wise registration. Let's denote a cortical surface dataset  $S = \{S_1, \dots, S_i, \dots, S_N\}$ , with  $N$  subjects and each subject  $i$  ( $i=1, \dots, N$ ) has multiple cortical attribute maps (such as average convexity, mean curvature, distance maps based on GyralNet and 3HGs, etc.). To successfully train the atlas synthesis network  $G_t$ , we formulate the baseline loss  $\mathcal{L}_{bs}$  as:

$$\mathcal{L}_{bs} = \sum_i \|S_i \circ \phi_i - A_t\|^2 + \lambda_c \|\bar{\mathbf{u}}\|^2 + \lambda_d \sum_i \|\mathbf{u}_i\|^2 + \lambda_s \sum_i \|\nabla \mathbf{u}_i\|^2.$$

The first term enforces the similarity of learned atlas and warped individual cortical feature maps, where  $\phi_i$  is the deformation field aligning the  $i$ -th surface to the atlas estimated by the registration network. The rest terms regularize the unbiasedness, extent, and smoothness of the tangent displacement field  $\mathbf{u}$ , respectively.  $\bar{\mathbf{u}}$  and  $\nabla$  denote for the average tangent displacement field and gradient operator. We formulate the spherical deformation field as in [17], which is an effective extension of diffeomorphic deformation from Euclidean space to spherical space. Briefly, given the predicted velocity field  $\mathbf{v}$  from the registration network, we can compute spherical deformation field  $\phi$  using six ‘‘scaling and squaring’’ layers [17], and then obtain the tangent displacement vector  $\mathbf{u} = \frac{\phi(\mathbf{x})}{\mathbf{x} \cdot \phi(\mathbf{x})} - \mathbf{x}$  from  $\mathbf{x}$  to  $\phi(\mathbf{x})$  on the sphere. After training the network successfully,  $G_t$  can yield on-demand atlas learned from the entire dataset.

### 2.3. Multi-level Spherical Registration Network

To flexibly and effectively incorporate multiple cortical features for surface registration, we introduce the ML-S3Reg architecture by stacking multiple S3Reg networks [17]. The S3Reg network is composed of spherical convolutions [16] which has demonstrated significant capability in learning the local spatial patterns for spherical registration. To better learn large deformations, we introduce the ML-S3Reg to break a large deformation into smaller ones by performing cortical registration in a coarse-to-fine manner using different cortical features at different levels. Fig. 3 shows an exemplar use of ML-S3Reg to obtain atlases with cortical folding features, i.e., ‘sulc’ (average convexity) and ‘curv’ (mean curvature), measuring cortical folding in a coarse and fine view, respectively. In this work, we stack four S3Reg networks at six levels (4, 5, 6, 6, 6, 6), with vertex counts of 2,562, 10,242, 40,962, 40,962, 40,962, and 40,962, to align sulc, sulc, sulc, curv, and distance maps of GyrNet and 3HGs, respectively. Finally, after training, the model infers the deformation fields for aligning cortical feature maps successively to the atlas generated by the synthesis network  $G_t$ . Notably, the generated atlas is deformed to the final atlas space using the learned deformation field derived by the last level.

## 3. EXPERIMENTS

### 3.1. Dataset and Preprocessing

We verify the effectiveness of our proposed framework based on the Human Connectome Project (HCP) S1200 release [20], including 1,089 structural MRI scans acquired from adults aged from 22 to 35 years. The image resolution is  $0.7 \times 0.7 \times 0.7 \text{ mm}^3$ . All structural images were processed by FreeSurfer [21], including co-registration, intensity inhomogeneity correction, skull stripping, cerebellum removal, tissue segmentation, hemispheres separation, topological correction, and surface reconstruction. The average convexity and mean curvature were computed for each vertex on the cortical surface as input. The GyrNet and 3HGs were extracted based on [4]. Then all spherical surfaces were further rigidly aligned onto the FreeSurfer atlas and resampled to have the same tessellation on the 6th subdivision of icosahedron with 40,962 vertices. In this work, 200 scans were randomly selected for testing, while the remaining 889 scans were used for training.

### 3.2. Experimental Settings

The generative model  $G_t$  for atlas synthesis consists of a fully connected layer with  $10,242 \times 3$  neurons, followed by a reshape and an upsampling layer, and three sequential blocks of “batch normalization [22] + spherical 1-ring convolution [16] + ReLU” with channel sizes of [8, 8, 4].  $G_t$  accepts age  $t$  as a scalar input, generating an age-conditioned atlas with dimensions of  $40,962 \times 4$ . For the registration network, we implement a smaller Spherical U-Net [16] model within S3Reg, stacking multiple instances for coarse-to-fine registration. This network includes three resolution levels and channels of [8, 16, 32], resulting in a compact design of only 0.5M parameters per S3Reg. The framework was implemented in PyTorch and optimized with Adam, using a weight decay of  $10^{-4}$  and cyclically tuning the learning rate between  $10^{-6}$  and  $10^{-3}$ . Training was capped at 500 epochs. Based on empirical comparison, we set the hyperparameters  $\lambda_c = 1.0$ ,  $\lambda_d = 4.0$ , and  $\lambda_s$  as 1.5, 2.5, and 4.0 at the 4th, 5th, and 6th levels, respectively.

Note that although our final model may appear large, it remains compact with only a small number of parameters, containing only 66K parameters in  $G_t$  and 6M parameters in ML-S3Reg. Meanwhile, it only requires 5s for one forward inference, including both atlas generation and individual-to-atlas registration, which is significantly faster than conventional atlas construction and registration methods, where the whole entire process can take several hours.

### 3.3. Validation and Results

To validate the advantage of our method for aligning cortical structural features, especially 3HG and GyrNet, we compared it with several popular cortical surface registration tools, such as FreeSurfer [9] and Spherical Demons (Demons) [10] both quantitatively and qualitatively. Specifically, for atlas generation, we calculated the average distance maps of 3HG and GyrNet to compare the spatial detailed patterns. For registration, we adopted the widely used metrics for evaluating the registration effectiveness, such as the mean Pearson's correlation coefficient between each pair of registered GyrNet feature maps in the testing sets. Moreover, to directly measure the alignment of 3HG and GyrNet in the representation of graphs, we further computed the average symmetric surface distance (ASSD) and mean intersection over union (IOU), characterizing the overlap and minimum distance between each pair of GyrNet and 3HG. Additionally, to validate how incorporating GyrNet and 3HG improves the registration of other morphological features, we introduce a variant of our proposed method that only uses average convexity and mean curvature for registration denoted as "Proposed- $\alpha$ ". Meanwhile, a baseline without registration is also provided to demonstrate the variance of cortical features in the native space and denoted as "w/o Reg".

In Fig. 4, we visually compared the average distance maps of GyrNet and 3HG across 200 subjects in the testing set. Our generated atlas reveals finer structural patterns in most cortical regions, especially in the zoomed-in area, underscoring the superior quality of the atlas. Table 1 presents the registration accuracy by different methods, evaluated by correlating individual feature maps. Our proposed framework demonstrates significantly improved performance over baseline methods for the distance maps of both GyrNet and 3HG. By incorporating GyrNet-related features, our approach yields a slight improvement in distance maps of 3HG and GyrNet, although there is a small decrease in average convexity ("Sulc") compared to "Proposed- $\alpha$ ", likely due to a trade-off between "Sulc" and 3HG distance map alignments. Nevertheless, our method achieves superior performance on Pearson's correlation coefficient for average convexity compared to other methods. In Table 2, registration effectiveness is assessed by directly comparing the spherical point and line distances for 3HG and GyrNet. Given the sparse distribution of 3HG points on the cortical surface, we consider two 3HG points as overlapping if their one-ring neighborhoods intersect. Consequently, we observe that the ASSD of 3HG is slightly larger than that of GyrNet. Even though, our proposed method still significantly outperforms other methods.

## 4. CONCLUSION

This study introduces a novel unsupervised learning framework that effectively addresses the challenges of aligning cortical 3HG and GyralNet structures across subjects. By transforming these cortical features into continuous distance maps on the spherical surface, we enabled their seamless integration within a registration network, thereby improving the alignment precision of cortical structural features between individuals and atlas. By jointly performing atlas generation and surface registration, we can achieve cortical surface registration across subjects without pre-defined atlas. To effectively handle large deformations, we introduce a multi-level spherical registration network (ML-S3Reg) with a coarse-to-fine approach that reduces computational load while capturing detailed cortical patterns. Experimental results on the HCP dataset validate the framework's ability to construct a high-resolution atlas for 3HG and GyralNet, advancing our study and understanding of complex cortical networks and their abnormalities in brain disorders.

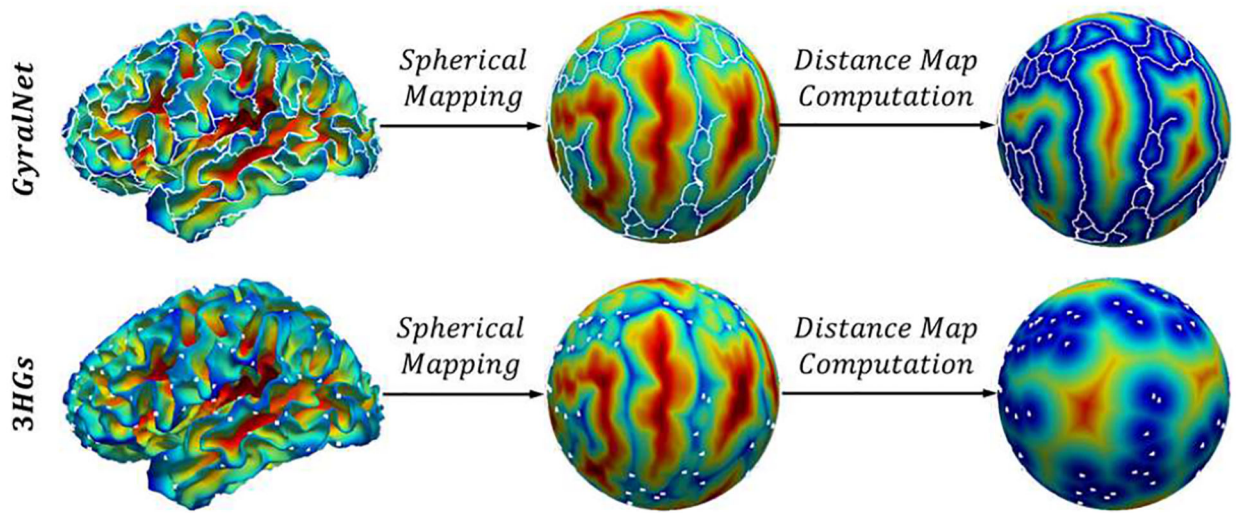
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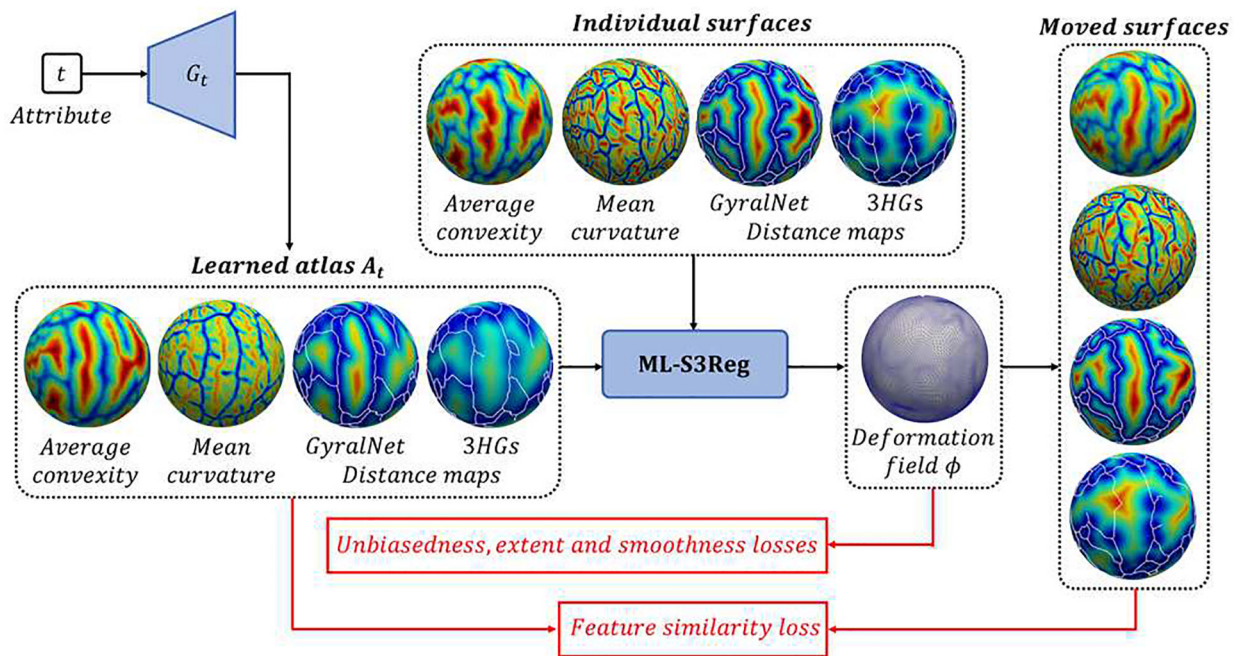
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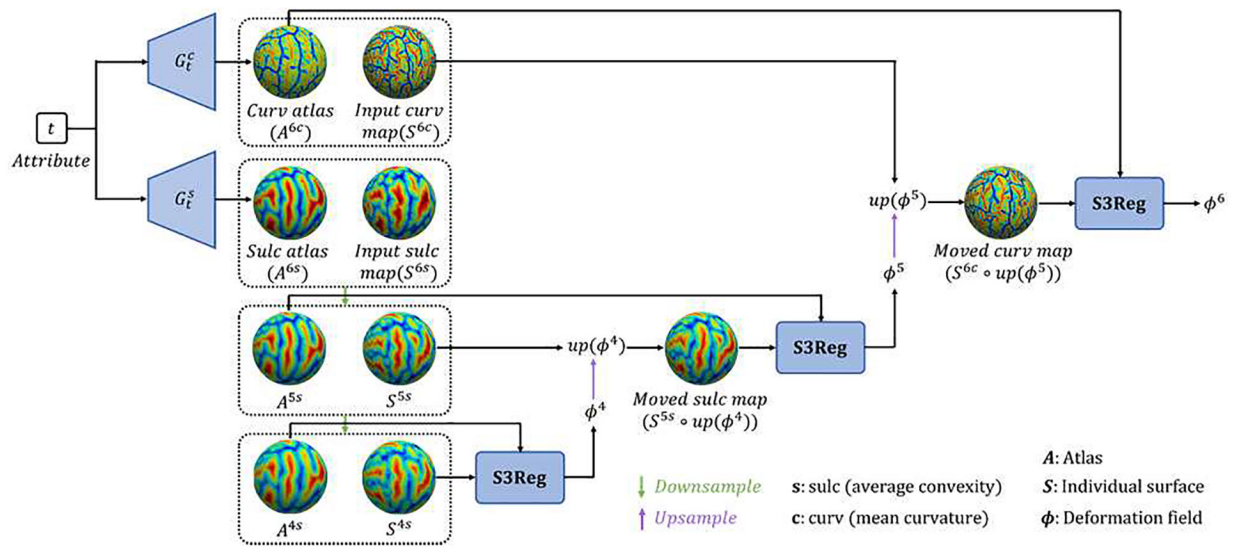
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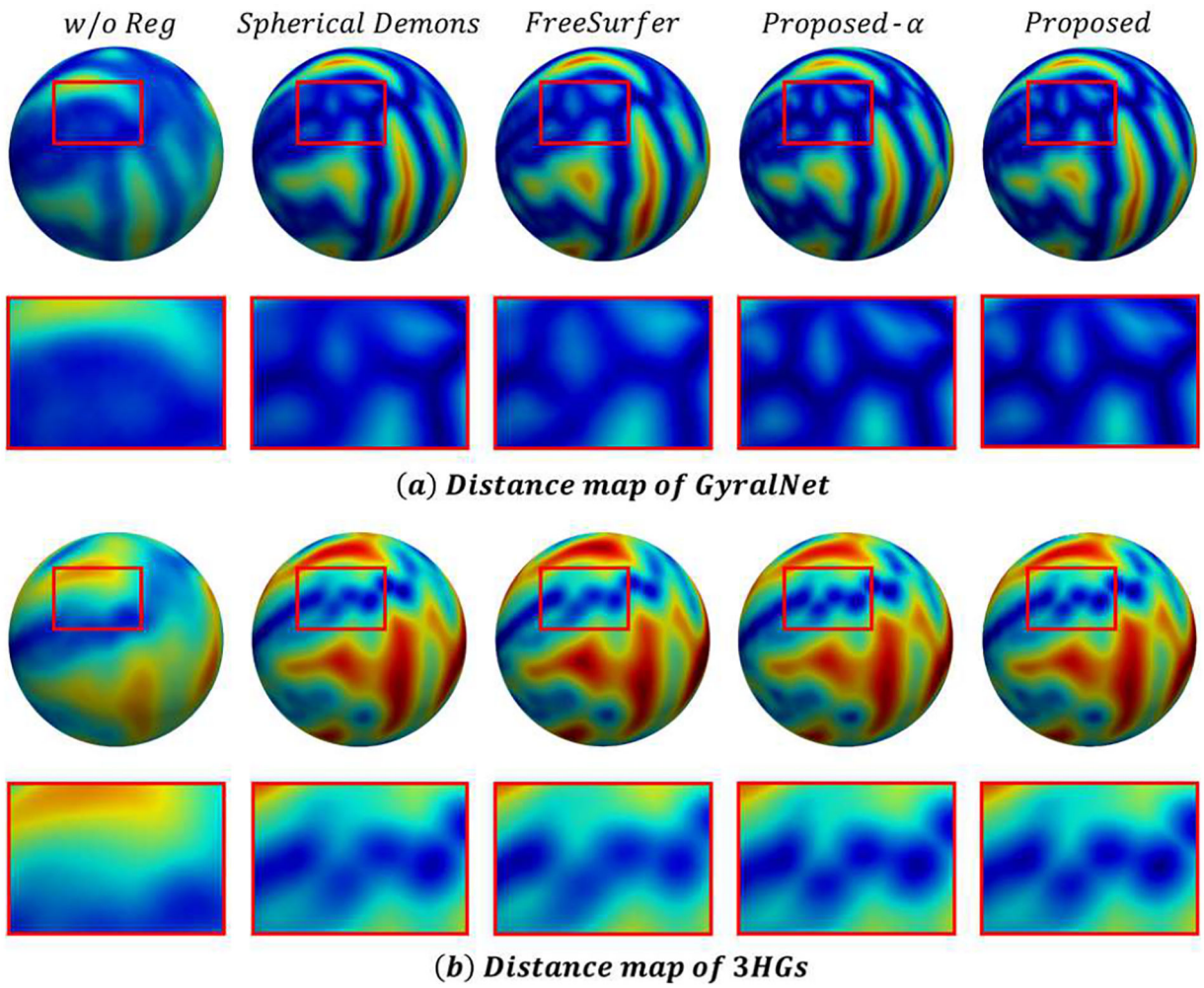
**Fig. 1.**  
Illustration of surface distance map generation.



**Fig. 2.** Overview of our unsupervised learning framework for aligning 3HG and GyrNet without a prior atlas. The atlas synthesis network takes attributes as input and outputs the learned atlases, which are then concatenated with the input individual surface to predict the deformation field using ML-S3Reg network (Fig. 3). The first distance map is generated based on GyrNet, while the second one is based on 3HG.



**Fig. 3.** Illustration of our ML-S3Reg architecture. The superscript numbers “6, 5, 4” denotes level-6, -5, and -4 cortical spheres, respectively. Note that this provides only a brief overview of our model, which can be flexibly extended to other levels and cortical features, such as the distance maps derived from GyrNet and 3HG.



**Fig. 4.** Group average distance maps of GyrNet and 3HG after registration using different methods.

**Table 1.**

Performance comparison of surface registration in terms of Pearson's correlation coefficient. "Sulc" denotes for average convexity.

Method	Sulc (%)	GyralNet	3HG
<i>w/o Reg</i>	45.58±10.47	49.00±8.91	45.58±10.47
<i>FreeSurfer</i>	81.05±2.14	72.14±4.11	65.54±6.03
<i>Demons</i>	77.04±2.69	75.96±3.70	65.76±5.57
<i>Proposed-a</i>	89.26±1.29	81.81±2.83	66.89±5.67
<b><i>Proposed</i></b>	<b>87.16±1.92</b>	<b>85.24±2.51 *</b>	<b>70.19±5.31 *</b>

\* indicates significantly improved results based on paired t-test with  $p < 0.05$ .

**Table 2.**

Performance comparison of surface registration in terms of IOU and ASSD.

	<b>Method</b>	<b>IOU (%)</b>	<b>ASSD (mm)</b>
<i>GyratNet</i>	<i>w/o Reg</i>	7.06±0.86	6.13±0.55
	<i>FreeSurfer</i>	13.99±1.08	4.51±0.31
	<i>Demons</i>	15.20±1.03	4.55±0.34
	<i>Proposed-<math>\alpha</math></i>	18.02±1.25	4.32±0.47
	<b><i>Proposed</i></b>	<b>22.99±1.59*</b>	<b>4.06±0.38*</b>
<i>3HG</i>	<i>w/o Reg</i>	6.92±1.28	11.52±0.78
	<i>FreeSurfer</i>	13.38±1.50	9.29±0.58
	<i>Demons</i>	12.92±1.42	9.48±0.59
	<i>Proposed-<math>\alpha</math></i>	15.96±1.57	9.03±0.67
	<b><i>Proposed</i></b>	<b>16.87±1.68*</b>	<b>8.83±0.69*</b>

\* indicates significantly improved results based on paired t-test with  $p < 0.05$ .