ANALYSIS OF SURFACE FOLDING PATTERNS OF DICCCOLS USING THE GPU-OPTIMIZED GEODESIC FIELD ESTIMATE

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Abstract. Localization of cortical regions of interests (ROIs) in the human brain via analysis of Diffusion Tensor Imaging (DTI) data plays a pivotal role in basic and clinical neuroscience. In recent studies, 358 common cortical landmarks in the human brain, termed as Dense Individualized and Common Connectivity-based Cortical Landmarks (DICCCOLs), have been identified. Each of these DICCCOL sites has been observed to possess fiber connection patterns that are consistent across individuals and populations and can be regarded as predictive of brain function. However, the regularity and variability of the cortical surface fold patterns at these DICCCOL sites have, thus far, not been investigated. This paper presents a novel approach, based on intrinsic surface geometry, for quantitative analysis of the regularity and variability of the cortical surface folding patterns with respect to the structural neural connectivity of the human brain. In particular, the Geodesic Field Estimate (GFE) is used to infer the relationship between the structural and connectional DTI features and the complex surface geometry of the human brain. A parallel algorithm, well suited for implementation on Graphics Processing Units (GPUs), is also proposed for efficient computation of the shortest geodesic paths between all cortical surface point pairs. Based on experimental results, a mathematical model for the morphological variability and regularity of the cortical folding patterns in the vicinity of the DICCCOL sites is proposed. It is envisioned that this model could be potentially applied in several human brain image registration and brain mapping applications.

1 Introduction

The increasing availability of Diffusion Tensor Imaging (DTI) data, has sparked a growing interest in assessing the structural differences in neural connectivity within cortical networks in diseased brains and healthy controls [4]. However, a fundamental issue is the localization of network nodes, or geometrically meaningful cortical regions of interest (ROIs), in the DTI datasets for assessment of

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structural connectivity. In particular, the complex surface geometry of the brain, manifest in the cortical surface folding patterns, provides important cues for the prediction of cortical cytostructure and function [2] thereby suggesting the regularity of cortical surface folding patterns. On the other hand, many studies demonstrate the remarkable variability of the cortical surface folding patterns and their inherent complex geometry [12].

The difficulty in formalizing a representation of the cortical surface folding patterns and establishing their correspondence across individual brains has hampered quantitative assessment of their geometric regularity and variability. Despite the paucity of quantitative evaluation, such a formal assessment is critical for several key research problems in human brain mapping such as, brain image registration, brain image segmentation, and cortical shape analysis. For instance, the problem of designing effective morphological or connectional features for brain image registration and segmentation would be very challenging without prior knowledge of the geometric regularity and variability of cortical surface folding patterns. In fact, such prior knowledge has been shown to be very useful for brain image registration [9] and could potentially benefit functional brain mapping via fMRI signal extraction and activation detection.

More recently, a dense map of 358 cortical landmarks, termed as Dense Individualized Common Connectivity-based Cortical Landmarks (DICCCOLs) [23], has been identified and validated. Each DICCCOL site possesses group-wise, consistent white matter fiber connection patterns which are also predictive of the cortical functions of the corresponding site [23]. Recent studies [23] have demonstrated the high reproducibility and predictability of DICCCOL sites in individual brains based on DTI data. However, the regularity and variability of the 358 DICCCOL sites with respect to the cortical surface geometry is yet to be fully explored. This paper examines the regularity and variability of the cortical surface folding patterns at the 358 DICCCOL sites where the cortical surface is reconstructed as a triangular mesh from the DTI data. A novel feature vector based on intrinsic surface geometry is employed to quantify the regularity and variability of the cortical surface geometry in the vicinity of each of the DICCCOL sites.

The Geodesic Field Estimate (GFE), a probability distribution of geodesic paths over a surface, has been shown to generate rich intrinsic geometric features of points on surface meshes [15]. These intrinsic geometric features are used to construct contextual surface descriptors around each of the 358 DICCCOL sites. The cumulative Mean Absolute Deviation (MAD) of the contextual surface descriptor is computed for each DICCCOL site across different subjects and is considered as the measure of variability of the cortical surface folding pattern at that DICCCOL site. A major issue for performing large-scale experiments with geodesic path-based surface descriptors is the computational complexity of geodesic path determination between all pairs of surface points. To address the computational complexity, a parallel version of the all-pairs geodesic path determination algorithm using GPUs is proposed and shown to be broadly applicable to other medical imaging domains as well.

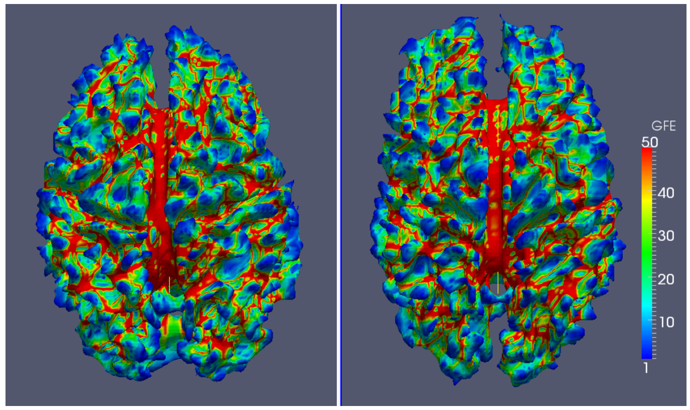

Fig. 1. Visualization of the GFE on cortical surfaces of two different subjects.

DTI data from 31 healthy young adult brains are used for this study. The experimental results demonstrate that some DICCCOL sites have significantly more regular cortical surface folding patterns than others. Overall, this study demonstrates the importance of geometric and morphological analysis of the complex cortical surface folding patterns which could be regarded as complementary to the fiber connection patterns in case of the more consistent DICCCOL sites. We envision that this study will offer novel insights into MRI-based versus DTI-based brain mapping methodologies, where multimodal registration, mapping and analysis is performed using both shape-based and connectivity-based features.

The main contributions of this paper are threefold. First, an intrinsic geometric surface signature, i.e., the GFE, is proposed for the characterization of geometric regularity and variability of DICCCOL cortical surface folding patterns. Second, a parallel version of the all-pairs geodesic path determination algorithm is designed and implemented using GPUs to ensure that the GFE computation is indeed scalable for large datasets. Third, the GPU-optimized GFE is applied successfully to the brain cortical brain surface for the first time.

The remainder of the paper is organized as follows: Section 2 discusses the related work. Section 3 presents the theoretical framework underlying the GFE-based surface descriptor. Issues pertaining to the parallelization and GPU implementation of the GFE computation are described in Section 4. Section 5 describes the data preparation procedure whereas Section 6 presents the results of experimental validation. Finally, Section 7 concludes the paper while outlining directions for future work.

2 Related Work

The surface folding patterns of the human cerebral cortex can be studied at varying scales, from a local neighborhood of a cortical landmark to the entire cortical surface. Analysis of local cortical surface folding patterns is typically based on computation of the local surface curvature whereas analysis of the folding pattern of the entire cortical surface or lobe of the human brain is based on computation of the Gyrification Index (GI) [24] or spherical wavelets [21]. More recently, surface descriptors for cortical surface folding have attracted great interest. Toro et al. [19] have proposed using the surface ratio thereby extending the description from a global scale, such as one obtained using the GI, to a local scale. Zhang et al. [22] have proposed a parametric representation of cortical surface folding patterns with strong local shape representation capability.

It is important to note that all the works mentioned above either do not exploit the intrinsic surface geometry or use very simple intrinsic geometric surface descriptors (such as local surface curvature). Rich and comprehensive descriptors based on intrinsic surface geometry, such as the Wave Kernel Signature [1], Heat Kernel Signature [17] and Discrete Surface Ricci Flow [25] have been widely used for shape representation and shape analysis in the computer graphics and computer vision communities. In this paper, we propose a surface descriptor, i.e., the GFE, based on intrinsic surface geometry for quantitative analysis of the regularity and variability of the brain cortical surface folding patterns with respect to structural neural connectivity.

3 Theoretical Derivation of the GFE

The shortest distance between two points on a complete Riemannian manifold is the length of the shortest geodesic path between them. The shortest geodesic path conveys rich information about the underlying manifold and, since it is based on intrinsic surface geometry, it is invariant to the coordinate space in which the manifold is embedded. However, determination of the shortest geodesic path is notoriously sensitive to small surface perturbations, making it difficult to use for robust shape analysis. To overcome this limitation, a novel GFE surface descriptor was proposed in [15]. The GFE for any point x on surface S can be defined as the probability of the shortest geodesic path between any two surface points p and q passing through x, i.e.,

$$GFE(x) = \mathrm{prob}(x \in GP(p, q)) \tag{1}$$

where, $GP(p, q)$ is the shortest geodesic path between points p and q and points $x, p, q \in S$. The GFE value at each surface point is computed using the all-pairs shortest geodesic path determination algorithm. The GFE has been shown to be a rich and stable surface descriptor that is well suited for robust shape analysis [15]. Intuitively, the GFE can be visualized as *ropes* threading the *valleys* of the shape as shown in Figure 1. Theoretically, the GFE is a special case of the more general *fuzzy geodesics* [18]. As a result, the GFE inherits the property of robustness to noise and surface perturbation from the fuzzy geodesics while being more concise and informative than the latter.

Theoretically, it has been shown that the stability of fuzzy geodesics can be quantified in terms of the Gromov-Hausdorff (GH) distance as the shape deforms [18]. The GH distance has been used to measure the extent of shape

```
KERNEL CUDA_Label_Correcting
tid ← getThreadID ∈ S, vid ← getBlockID ∈ V
for all neighbors nid of vid do
    if C[vid,tid] > C[nid,tid] + W[nid] then
        C[vid,tid] ← C[nid,tid] + W[nid]
        Pred[vid,tid] ← nid
        Terminate ← false
    end if
end for
```

(a)

(b)

Fig. 2. Instant update/propagate strategy for computing the all-pairs shortest path problem on a GPU: (a) the GPU Kernel (b) execution example on GPU Grid. The updated distance cost is instantly reused by the subsequent block computations. This example assumes there are four streaming multiprocessors, each executing one block at a time.

deformation [14]. It has been shown that two shapes with a small GH distance have a provably small difference in their respective fuzzy geodesics which ensures a similar property in the case of the GFE [18]. In particular, a tight bound for the fuzzy geodesics in terms of noise has been provided which holds true for the special case of the GFE [18]. Moreover, to make the GFE robust to noise, we normalized the GFE with the area of the triangle when using a triangulated mesh-based representation of the underlying brain cortical surface.

4 Implementation

The high computational complexity of the all-pairs shortest geodesic path determination algorithm renders the use of the GFE highly impractical for most medical image analysis problems. A typical graph generated from the brain cortical surface mesh has a large number of nodes/vertices (40,000 - 50,000) but a relatively small number of edges (240,000 - 300,000). Also, the corresponding shortest-path search trees (where the root is the source node) are very deep and narrow since every node's connections are limited to its local neighbors with no shortcuts to reach farther nodes. We propose and implement a novel instant update/propagate algorithm, described in Figure 2, that is optimized for such search trees. Our algorithm utilizes GPUs more efficiently by letting the search propagate to multiple levels in the search tree before global synchronization. A task parallel scheme [16] is adopted for computing multiple search trees originating from N different source points simultaneously, thus allowing for more efficient memory access patterns.

5 Data Preparation

DTI data from 31 young adults from a publicly available database [20] are used. The DICCCOL sites and connectomes identified and constructed from these

DTI data [23] are regarded as the ground truth. The DTI data preprocessing is performed using the FSL software suite [5] which includes eddy current correction, skull removal, computing the Fractional Anisotropy (FA) image, and tissue segmentation. The cortical surface is reconstructed using the segmented FA image followed by fiber tracking performed using MedINRIA [10]. The DICCCOL sites and connectomes are obtained from the preprocessed data using publicly available programs (http://dicccol.cs.uga.edu/).

In the DICCCOL framework, all the cortical landmarks are defined and predicted using DTI data. Therefore, the mapping of DTI-derived DICCCOL sites onto the MNI/Talairach atlas image has to rely on MR image registration techniques. Given the 358 DICCCOL sites from ten template brains with the corresponding structural MR images, the DICCCOL sites in each DT image of the template brains are registered with the corresponding MR images and warped onto the MNI template using the FSL FLIRT software tool [6] since it was observed to perform better than the alternatives [8]. Since there is no ground truth data for evaluating the correspondence of the DICCCOL sites with the MNI atlas image, the performance of the image registration algorithm is assessed in terms of consistency resulting in a slightly higher accuracy for FSL FLIRT (6.29 mm) when compared to the alternatives [8].

6 Experimental Results

6.1 Speedup results

The parallel GFE computation on a GPU was observed to achieve a speedup of 14 over its optimized CPU implementation (Johnson's algorithm in the Boost C++ library http://www.boost.org/), taking less than a minute for each subject. The GFE computation was performed on a PC workstation with an NVIDIA GTX 480 GPU and an Intel Core i5-2400 CPU clocked at 3.4 GHz. Figure 3 demonstrates the speedup resulting from the GPU-optimized GFE computation on surface mesh graphs from the SHREC 2010 dataset [13].

6.2 Experimental validation on simple surfaces

To the best of our knowledge, this is one of the first attempts to study the problem of surface regularity and variability at cortical surface ROI sites. The proposed GFE signature is evaluated on simple surfaces to ensure its uniqueness at specific surface points as well as its regularity at symmetric surface points. One specific example is shown in Figure 4 where the proposed GFE signature is observed to successfully differentiate between the regularity and variability of the *wolf* object surface.

6.3 Construction of the GFE-based feature vector

A GFE contextual histogram (GCH) is computed for each DICCCOL site as follows. A local neighborhood (i.e., ROI) for each DICCCOL site, comprising of the geodesically closest 50 surface points, is constructed. A 10-bin histogram of GFE values (i.e, the GCH) is generated for the ROI and represented as a 10-tuple

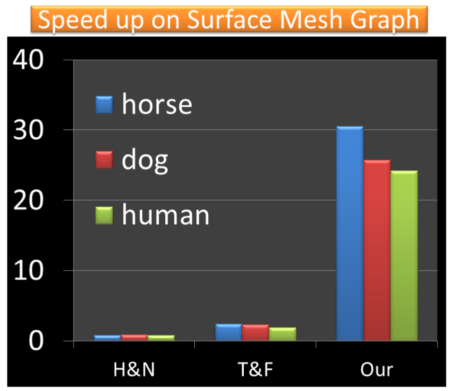

Fig. 3. Visualization of the speedup resulting from GPU-based optimization. Typically, a 25-30 times speedup is achieved by the proposed method (Our) for SHREC 2010 [13] dataset meshes (eg. *horse*, *dog* and *human*) with approximately 30000 - 50000 vertices. The typical speedups achieved by methods proposed by Harish et. al. (H&N) [3] and Okuyama et. al. (T&F) [16] for the same meshes are also compared.

feature vector. The GCH feature vector at DICCCOL site x is formally denoted by $GCH^{10}(x)$. Figure 5 shows similar GCH feature values across 5 subjects for a relatively regular DICCCOL site ROI #234 and very dissimilar GCH feature values across the same 5 subjects for a relatively irregular DICCCOL site ROI #80.

6.4 Cumulative mean absolute deviation for measuring variability

The similarities of the GCH feature values for 358 DICCCOL site ROIs across 31 subjects are quantified by the cumulative mean absolute deviation (MAD) and shown as blue curves in Figure 6. It is evident that there is substantial variability across the ROIs in terms of the regularity/variability of their corresponding cortical folding patterns across the subject cohort. For instance, some ROIs, such as ROI #234, #94, show greater similarity in terms of surface geometry across the 31 subjects, whereas other ROIs, such as ROI #80, #252, exhibit greater variability across the same subject cohort. Based on the cumulative MAD values computed across 31 subjects, the top 5 percentile ROIs are considered as the most variable and irregular across the subject cohort whereas bottom 5 percentile ROIs are considered the most regular. These ROIs are plotted in Figure 7 which reveal an interesting observation. The more geometrically stable ROIs are found towards the outer surface of the cerebral cortex whereas the least stable ones are found around the center.

7 Conclusions and Future Directions

A novel surface feature based on intrinsic geometry is proposed for analysis of cortical surface folding patterns at the DICCCOL sites in the human brain. Our

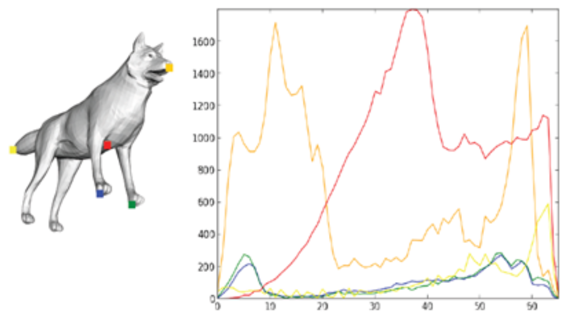

Fig. 4. Visualization of regularity and uniqueness of GFE signature on the simpler *wolf* object surface.

study sheds new light on the relationship between the geometric regularity and structural regularity at DICCCOL sites within the cerebral cortex. Our study indicates that further research in morphological analysis of cortical surface folding patterns is needed. Specifically, the relative positions of the geometrically regular and geometrically variable DICCCOL sites within the cerebral cortex deserve more extensive and rigorous investigation. We plan to examine the possibility of using both, the cortical surface folding patterns and DTI-derived connectivity patterns to predict the locations of DICCCOL sites within individual brains, which could then be used for brain registration and mapping.

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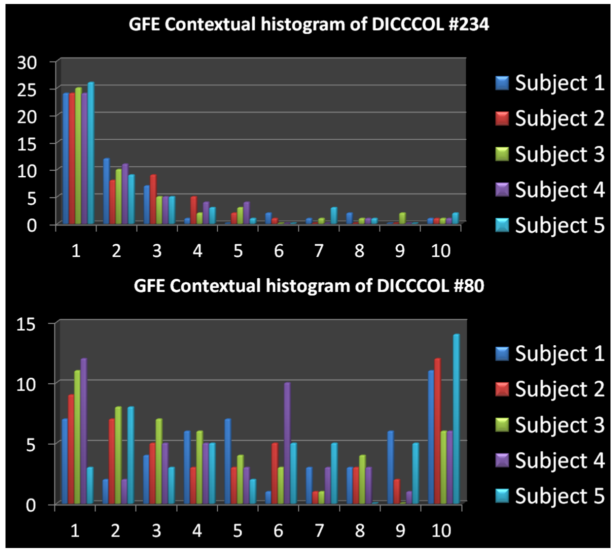

Fig. 5. Visualization of the GFE context histogram at two DICCCOL sites for 5 different subjects.

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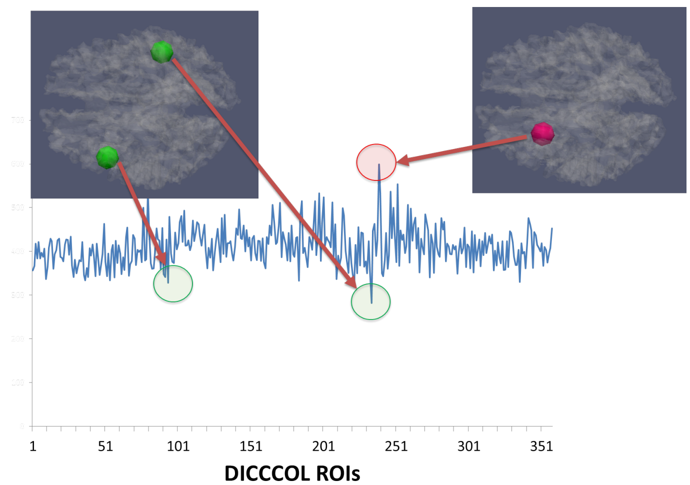

Fig. 6. Plot of cumulative MAD values for the 358 DICCCOL site ROIs where lower MAD values denote higher regularity. Two DICCCOL site ROIs with higher regularity (green) and one DICCCOL site ROI with higher variability (red) are shown.

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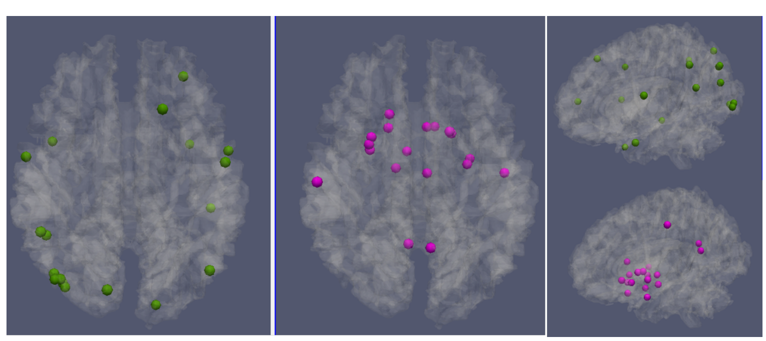

Fig. 7. ROIs with cumulative MAD values in the bottom 5 percentile (regular) are plotted in green whereas ROIs with cumulative MAD values in the top 5 percentile (variable and irregular) are plotted in pink.