Distance Networks for Morphological Profiling and Characterization of DICCCOL Landmarks

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Abstract. In recent works, 358 cortical landmarks named Dense Individualized Common Connectivity based Cortical Landmarks (DICCCOLs) were identified. Instead of whole-brain parcellation into sub-units, it identified the common brain regions that preserve consistent structural connectivity profile based diffusion tensor imaging (DTI). However, since the DICCCOL system was developed based on connectivity patterns only, morphological and geometric features were not used. Thus, in this paper, we constructed distance networks based on both geodesic distance and Euclidean distance to morphologically profile and characterize DICCCOL landmarks. Based on the distance network derived from 10 templates subjects with DICCCOL, we evaluated the anatomic consistency of each DICCCOL, identified reliable/unreliable DICCCOLs, and modeled the distance network of DICCCOLs. Our results suggested that the most relative consistent connections are long distance connections. Also, both of the distance measurements gave consistent observations and worked well in identifying anatomical consistent and inconsistent DICCCOLs. In the future, distance networks can be potentially applied as a complementary metric to improve the prediction accuracy of DICCCOLs or other ROIs defined on cortical surface.

Keywords: cortical landmark, DICCCOL, geodesic distance, Euclidean distance, ROIs

1 Introduction

In a previous work, Zhu *et al.* identified 358 brain landmarks that are consistently preserved across individuals named Dense Individualized Common Connectivity based Cortical Landmarks (DICCCOLs) [1]. Instead of whole-brain parcellation into sub-units, these DICCCOLs landmarks aim to identify the common brain regions that preserve consistent structural connectivity profile based diffusion tensor imaging (DTI) (section 2.2). It has been shown that these landmarks can be applied as network nodes that possess correspondence across individuals to investigate brain functional/structural networks [2]. However, despite that it is an important contribution to

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human brain mapping field, several limitations of current DICCCOL framework had also been identified [3]. Firstly, different brain anatomic regions may also generate similar DTI derived axonal fiber connection profiles and the proposed tracemap descriptor [1] might not be able to differentiate these brain regions in such cases. Secondly, since DICCCOL is obtained by data driven approaches and the training process only searches the neighbor regions for the optimal locations of DICCCOLs (section 2.2), some DICCCOLs may converge to the local minimum during the search process. Due to these limitations, the same DICCCOL may converge to different anatomical locations during training and prediction process. Though three experts visually inspect the results to eliminate those connectionally or anatomically inconsistent landmarks before generating the finalized DICCCOLs, due to the unavoidable subjective judgments and the experts' possible mistakes, there still might be unreliable ROIs embedded in the template of the current DICCCOL system.

In the literature, distance measurement has been shown to be promising in characterizing brain anatomies. In [4], the geodesic distances (GDs) between landmarks were applied to characterize and extract structures on the cortex. In [5], the authors extracted sulci fundi on cerebral cortex based on the geodesic characteristics. In [6] and [7], the Euclidean distance (ED) was applied to investigate and characterize the spatial relationships between the brain's functional regions. GD is powerful in describing anatomical correlations between cortical landmarks since the neocortex of human brain is highly convoluted and the brain anatomy also correlates with cortical folding patterns in a certain degree (**Fig. 1**(a)). Meanwhile, ED is simple to compute and does not rely on surface reconstruction quality (**Fig. 1**(a)). Since the DICCCOL system was developed mainly based on the connectivity patterns, morphological and geometric features were not used. Therefore, GDs and EDs between DICCCOLs can be possibly applied to construct distance networks as a complementary metric to improve DICCCOL.

By constructing distance networks of DICCCOLs in the 10 templates subjects and comparing the variability and regularity of these 10 networks, we evaluate the anatomical consistency of each DICCCOL, identify reliable/unreliable DICCCOLs, and model the distance network of DICCCOLs. Intriguingly, our result showed that the most consistent distance edges are the long global distance connections while the most inconsistent edges are local connections. Also, the distance networks based ED and GD gave quite similar observations and performed accurately in identifying anatomical consistent or inconsistent DICCCOLs. By adding this distance network as a new constraint of DICCCOL, the reliability of DICCCOL system could be increased in the future in both modeling common cortical landmarks and predicting these landmarks in new subject's brain.

2 Method

2.1 Experimental Data

The DTI data downloaded from DICCCOL website (http://dicccol.cs.uga.edu/) which was applied in the development and the definition of DICCCOLs was applied in this study. As described in Zhu *et al.*'s paper [1], the scans were performed on a GE 3T Sigma MRI system using an 8-channel head coil. The acquisition parameters are: matrix size = 128×128, 60 slices, image resolution = 2×2×2mm isotropic, TR=15s, ASSET=2, 3 B0 images, 30 optimized gradient directions, b-value=0/1000. Acquired data were preprocessed via the preprocessing pipeline of DICCCOL as described in [1] which includes eddy current correction, skull removal, computing FA image [8], GM/WM segmentation [9], WM surface reconstruction [10], and streamline fiber tracking [11].

2.2 DICCCOL

DICCCOLs were originally developed by data-driven approaches [1]. In brief, training subjects were aligned to the same space by linear image registration. 2056 vertices on the reconstructed cortical surfaces were randomly selected as initial ROIs and the correspondence was assigned to the vertices from different subjects that are spatially close to each other. Then each initial ROI was moved around to maximize the similarity of its DTI connection profile to the profile of corresponding ROIs. By doing so iteratively, all those ROIs finally converged to a location that the similarity was maximized. Such process was performed in two groups of subjects independently. Then by comparing the converged ROIs in these two groups based on the quantitative measurement and the advice from three experts, the ones with similarity in both spatial location and connection profile were picked as DICCCOLs. Finally, 358 DICCCOLs were picked and the 10 subjects used for training were taken as the template [1].

To predict DICCCOLs on new individuals, the brain of the individual were rigidly aligned to the templates' space. The location of each DICCCOL in the template brains were taken as the initial location. Then a search was run in its neighborhood [1] on the cortical surface and the location of DICCCOL on the new subject was determined as the region that most resemble the connection profile of the template.

2.3 Geodesic Distance

We applied the method based on fast matching proposed in [5, 12] to find the shortest path between DICCCOLs on the reconstructed cortical surface and estimate geodesic distance between them. Generally, by assigning speed F(x) to each vertex x on surface, a closed curve evolves and expands on the surface starting from a source vertex in a manner of 'wave'. During this procedure, we record the arrival time T(x) of a vertex x that the 'wave' takes to travel from the source vertex. This problem is solved by equation in [2]:

$$\left|\nabla T(x)\right| F(x) = 1, x \in S \tag{1}$$

where S represents the surface. In this paper, we set $F(x)$ to be '1' for all vertices, so that arrival time $T(x)$ is equivalent to the geodesic distance between the two vertices.

2.4 Distance Network Variability

For each pair of DICCCOLs, the GD and ED between them were computed. By taking DICCCOLs as network nodes and GD/ED as the edges between nodes, a distance network can be constructed for DICCCOLs in each individual's brain. By examining the consistency of this network between templates, we could evaluate the anatomical consistency of each DICCCOL, identify reliable/unreliable DICCCOLs, and model the distance network of DICCCOLs. The evaluation was performed based on GD network and ED network separately and by comparing the outcome of each network, the performance of ED/GD as distance constrain for cortical landmarks will be discussed. Specifically, the mean value of each edge among 10 template subjects and the corresponding standard deviations were obtained. Intuitively, since GD is larger than ED, the standard deviation of GD is also larger than ED on average which makes it difficult to compare these two measurements. Thus in this paper, we applied relative standard deviation as a measurement of the variability of edges:

$$Var(E) = E_{std} / \overline{E} \tag{2}$$

where E is the edge to measure, Estd and $\overline{E}$ are the standard deviation and mean of its length.

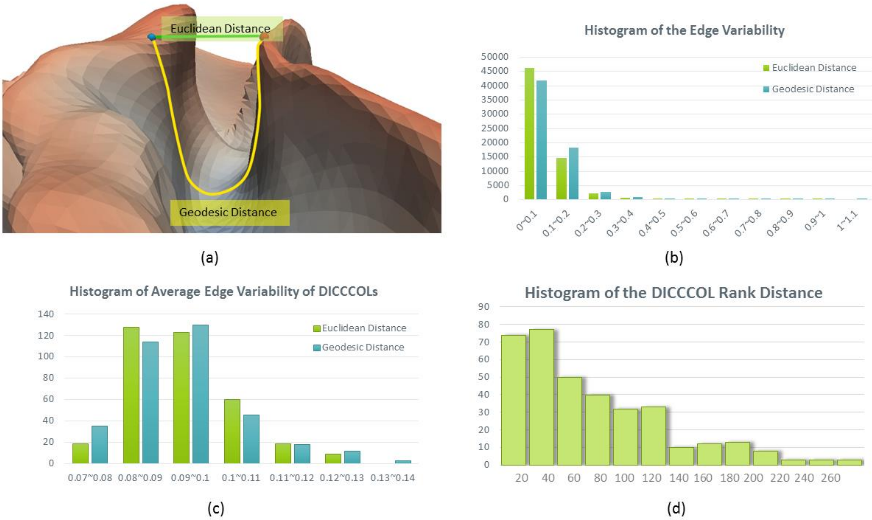

Fig. 1. (a) Illustration of geodesic distance (GD) and Euclidean distance (ED) between two ROIs. (b) Histogram of the variability of the edges in 10 templates' brains. (c) Histogram of the average edge variability of the DICCCOLs among templates. (d) Histogram of the distance between DICCCOL consistency ranks.

3 Results

Firstly, we compute the DICCCOLs' distance network in the brains of templates. The distributions of the variability of GD and ED are quite similar (Fig. 1(b)). Intriguingly, the most consistent edges are long distance connections while (Fig. 2(a)-(b)) the most inconsistent edges are local connections (Fig. 2(c)-(d)). This is partially due to the relative deviation we applied for analysis. Moreover, the spatial distributions of consistent/inconsistent GD/ED edges are quite similar (Fig. 2, Table 1, Table 2). The edges within occipital lobes are the most inconsistent while the edges between occipital lobes and frontal lobes are the most consistent.

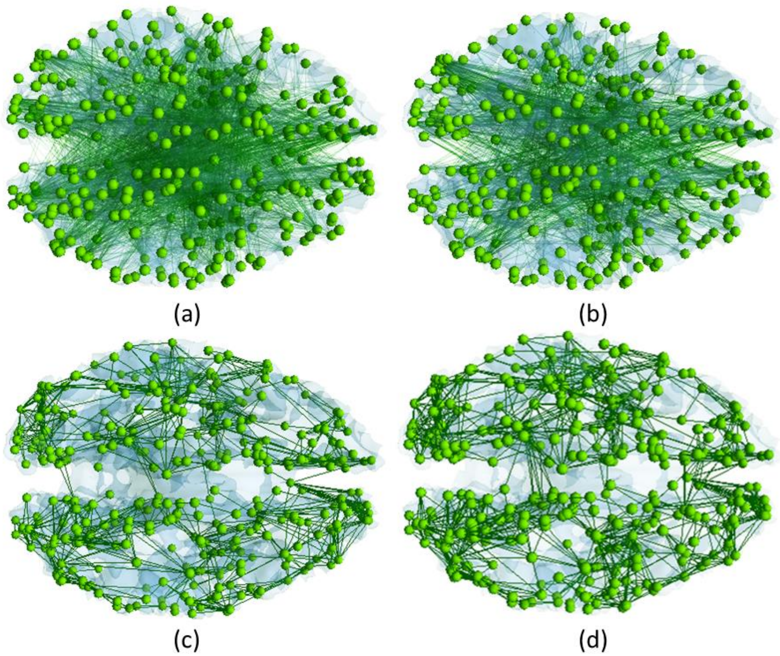

Fig. 2. Visualization of the edges that (a) have relatively small ED variability (<0.04); (b) have relatively small GD variability (<0.04); (c) have relatively large ED variability (>0.3); (d) have relatively large GD variability (>0.3).

Then for each DICCCOL, the average variability of the edges ($\overline{E_{var}}$) connected to it were calculated (Fig. 3). By assuming that the DICCCOLs with consistent anatomy should stay at the same location across brains and thus the edges connected to it should be similar across individuals, those DICCCOLs with smaller $\overline{E_{var}}$ could be more reliable than those with larger $\overline{E_{var}}$. We ranked the DICCCOLs in ascending order based on $\overline{E_{var}}$ of GD and Ed separately. The ranking results are quite similar between two different measurements as revealed by the histogram in Fig. 1(d). To examine and compare the performance of GD and ED in identifying the anatomy consistent and the reliable DICCCOLs, we visualized certain DICCCOLs that are agreed or disagreed by GD/ED on 10 templates' cortical surfaces in **Fig. 4**. DICCCOL #245 is agreed by both measurements to be one of the most consistent landmarks while #290 is agreed to be one of the most inconsistent one. By visual check, #290's location truly varies across templates as highlighted by arrows with different colors, while #245 is relatively consistent across templates. #312/#4 was indicated to be inconsistent by ED/GD only. However, as highlighted by the arrows with different colors, these DICCCOLs are also relatively anatomically inconsistent across templates. These observations suggested that both GD and ED can be applied as distance constraints for brain landmarks and they are complementary to each other.

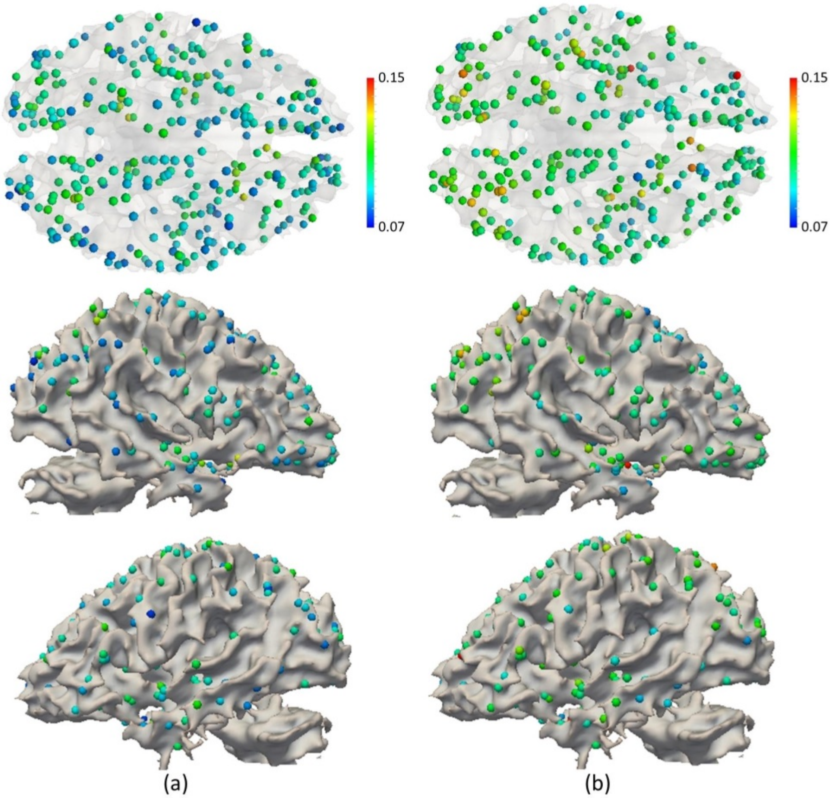

Fig. 3. Visualization of DICCCOLs in one template brain color-coded by the average standard deviations of (a) ED or (b) GD from each DICCCOL to the rest DICCCOLs in 10 template subjects.

Table 1. Average standard deviations of the ED between DICCCOLs within or between lobes.

	Frontal	Parietal	Temporal	Limbic	Occipital
Frontal	0.1130	0.0820	0.0798	0.0952	0.0659
Parietal	0.0820	0.1245	0.0972	0.0839	0.1090
Temporal	0.0798	0.0972	0.1184	0.0960	0.0891
Limbic	0.0952	0.0839	0.0960	0.1497	0.0846
Occipital	0.0659	0.1090	0.0891	0.0846	0.1683

Table 2. Average standard deviations of the GD between DICCCOLs within or between lobes.

	Frontal	Parietal	Temporal	Limbic	Occipital
Frontal	0.1240	0.0898	0.0860	0.0966	0.0720
Parietal	0.0898	0.1412	0.1081	0.0949	0.1314
Temporal	0.0860	0.1081	0.1282	0.1011	0.1020
Limbic	0.0966	0.0949	0.1011	0.1482	0.0993
Occipital	0.0720	0.1314	0.1020	0.0993	0.2029

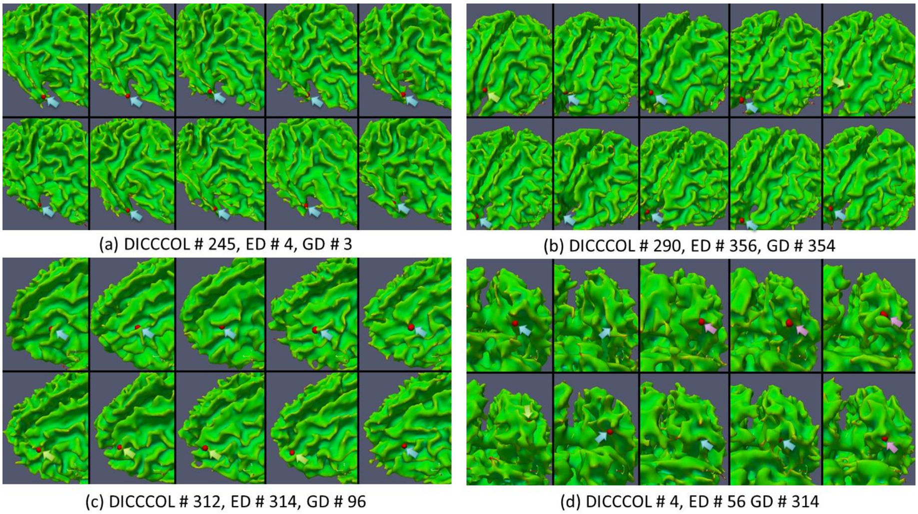

Fig. 4. Visualization of four DICCCOLs (bubble) on the cortical surfaces of 10 templates. The DICCCOL ID and its consistency rank by different distance measurement are listed below each sub-figure.

4 Conclusion

In this paper, we analyzed the morphological profile and character of DICCCOL landmarks based on distance networks. The distance network based on different distance measurements gave similar observations in our experiments. Intriguingly, the long distance connections are more reliable than local connections. By comparing the consistency of distance networks, the errors and anatomical inconsistent DICCCOLs in the templates were also identified. Since DICCCOL system was developed based on the structural connectivity network, our results showed that distance network could be a useful, complementary metric of the DICCCOL system. In the future, we will improve the reliability of DICCCOL models and the accuracy of DICCCOL prediction by integrating distance network into the DICCCOL framework. And the improved framework will be applied to analyze brain diseases.

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