Designing Consistent Cortical Surface Features

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Introduction

In cortical surface analysis, a common challenge is designing new features that can enhance statistical power and effectively discriminate clinical populations. This task is particularly difficult due to the absence of ground truth. In such scenarios, we discuss a methods to construct consistent features that can significantly improve signal detection power.

Hemisphere Consistency

Since cortical surface data lacks ground truth, we can use the consistency of cortical measures across the left and right hemispheres as a benchmark. Although there are hemispheric variations, these differences are typically smaller within a single subject than between different subjects. Therefore, the correlation of measures between hemispheres serves as a reliability metric. This differs from the traditional asymmetry index, which highlights the hemispheric differences.

Fig. 1. Extracted sulcal trees are flattened for better visualization. We are interested in designing a robust feature that will be used for a population study on sulcal trees.

Example 1 (Degree-based entropy). *There are 101 healthy controls, 50 unaffected relatives of schizophrenia patients, and 101 first-episode psychosis patients (Choi et al., 2022). We are interested designing robust Entropy features on sucal trees for ANOVA (Fig. 1).*

Entropy measures the data's complexity across different scales – from local (individual nodes) to global (the entire graphs). For node degree i, and its frequency f_i across a graph is calculated. This frequency is normalized to form a probability distribution p_i, i.e.,

$$p_i = \frac{f_i}{\sum_i f_i}.$$

Then its entropy H is computed as

$$H = -\sum_i p_i \log_2 p_i.$$

For sulcal and gyral trees (Huang et al., 2020), degree-based entropy is not reliable, as evidenced by a correlation of 0.293 across all subjects (Fig. 2). Since sulcal/gyral trees have a maximum degree of 3, they only present two states of probability (degrees 2 and 3), and entropy cannot be computed consistently even within a subject. Therefore, in more complex population studies such as ANOVA (Table 1), **degree-based entropy will not perform well**.

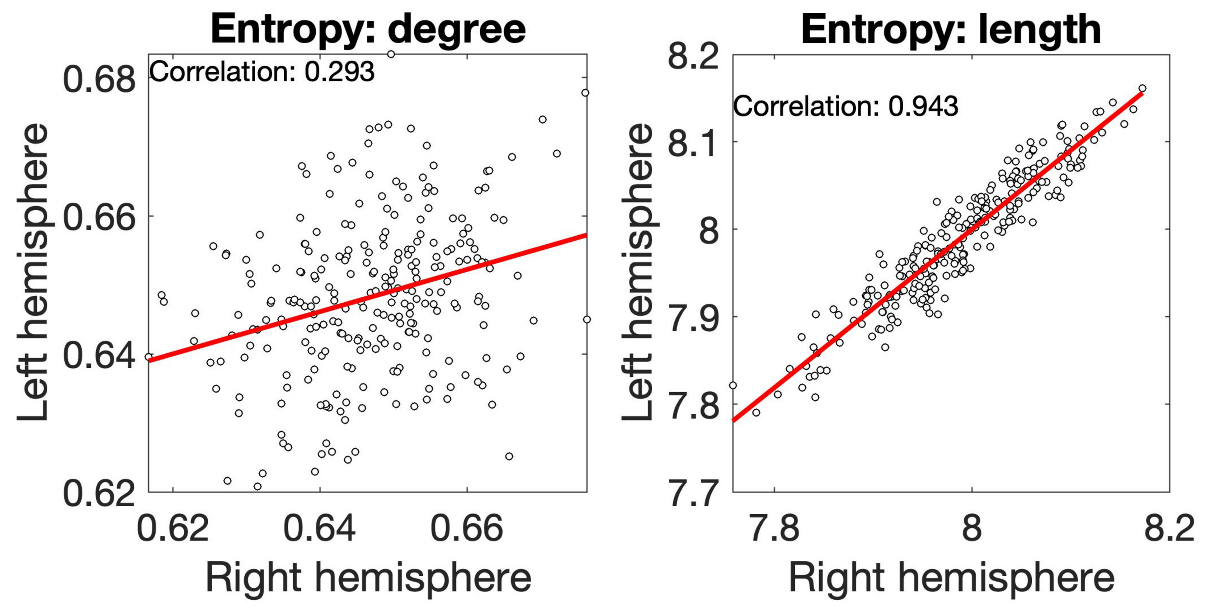
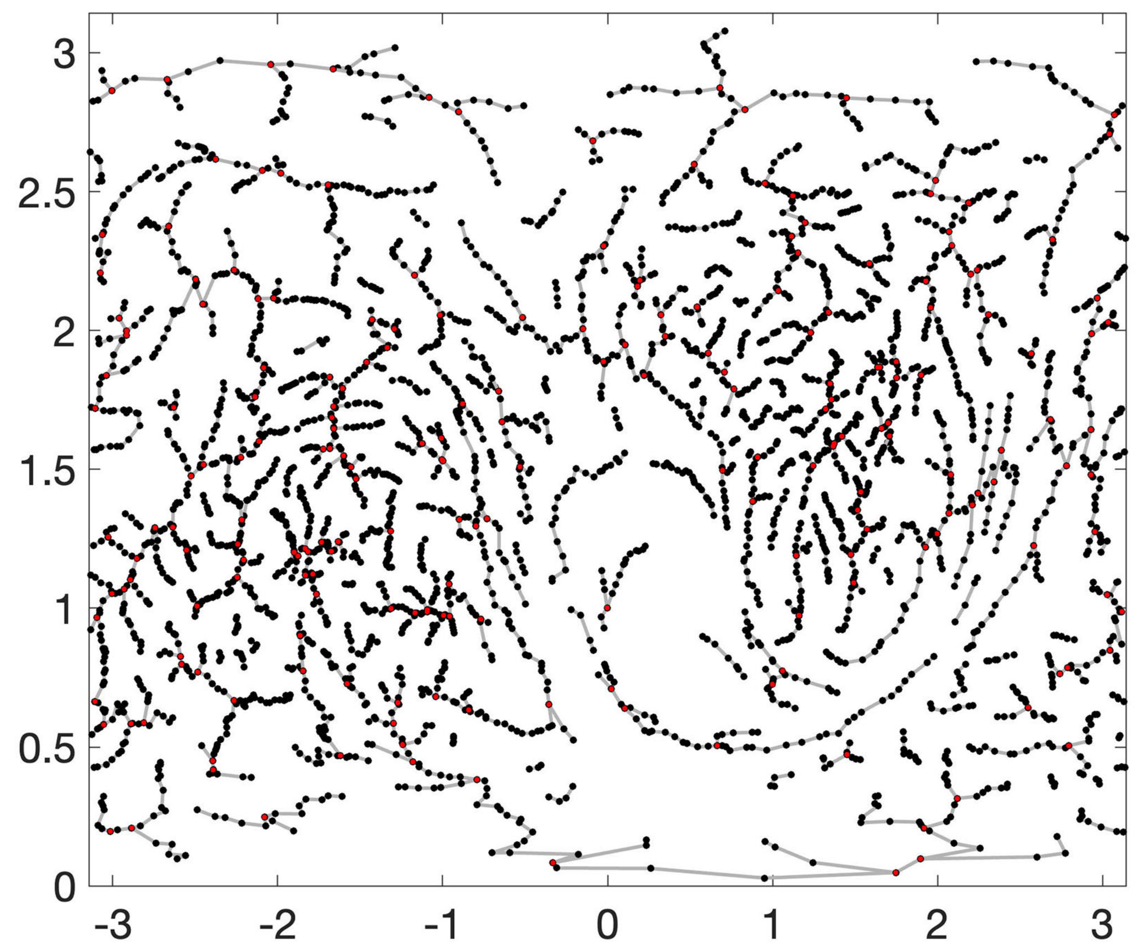


Fig. 2 displays the hemisphere consistency measured by the correlation between hemispheres, which indicates the consistency and reliability of a measurement. With very low correlation, degree-based entropy will not be a useful feature in a population study.



Measures	Variation	F-stat	p-value
Entropy - Degree: Left	Group	0.1842	0.8319
	Sex	1.2988	0.2555
	Age	2.7088	0.1011
Entropy - Degree: Right	Group	1.7866	0.1697
	Sex	6.8876	0.0092
	Age	3.4770	0.0634
Entropy - Length: Left	Group	2.5810	0.0777
	Sex	124.9552	0.0001
	Age	7.9879	0.0051
Entropy - Length: Right	Group	2.2233	0.1104
	Sex	119.8195	0.0001
	Age	7.3176	0.0073

Table 1. ANOVA results for Group, Sex, and Age variables on entropy measures along sulci and gyri. As expected, degree-based entropy does not perform as well as length-based entropy.

Example 2 (Length-based entropy). *We investigated if length-based entropy is more consistent feature using the same data as Example 1.*

For length-based entropy, we sort edge weights over a graph and build an order statistic:

$$w_{(1)} \leq w_{(2)} \leq \cdots \leq w_{(q-1)} \leq w_{(q)}.$$

Then the probability is given by

$$p_i = \frac{\sum_{j=1}^{q} \delta_{w_{(i)},w_{(j)}}}{q}$$

with the Kronecker delta δ_{xy}. The entropy is computed similarly. Length-based entropy exhibits a high correlaton 0.943 (Fig. 2). Therefore, **length-based entropy will yield more reliable statistical results** than the degree-based entropy as demonstrated in ANOVA (Table 1.)

Example 3 (White matter fiber density). *In a study with 358 healthy subjects with both T1-MRI and diffusion-MRI (Chung et al., 2019), we explored designing consistent fiber measures across sulci and gyri to test the effects of sex, age, and intelligence.*

The tract density is computed as the number of tracts within a 2mm radius around each node (Fig. 3). The hemispheric correlation is 0.457 in sulci and 0.419 for gyri. **Tract density is partially useful** for detecting sex differences, but is less useful for complex cognitive analysis (Table 2).

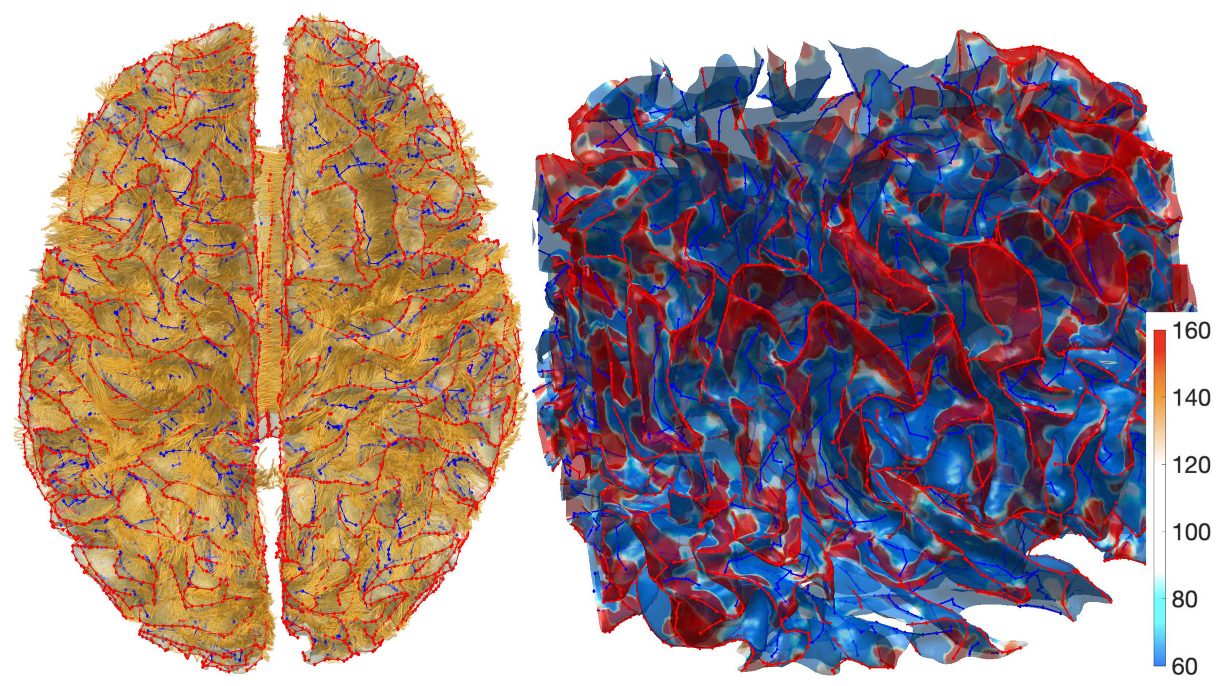


Fig. 3. Left: Extracted white matter fiber tracts are superimposed on top of sulcal and gyral trees. Right: Number of tracts within 2mm radius of nodes of trees are computed.

Measures	Variation	F-stat	p-value
Tract density: Left Sulci	Sex	30.6484	6.02e-08
	Age	2.5504	0.0555
	Intelligence	1.0037	0.4560
Tract density: Right Sulci	Sex	3.2813	0.0709
	Age	0.4298	0.7317
	Intelligence	1.2750	0.1970
Tract Density: Left Gyri	Sex	7.5566	0.0063
	Age	1.0994	0.3494
	Intelligence	0.7485	0.7672
Tract Density: Right Gyri	Sex	17.0690	4.50e-05
	Age	1.0363	0.3765
	Intelligence	0.8516	0.6440

Table 2. ANOVA results for Sex, Age, and Fluid Intelligence on tract density along the nodes of sulci and gyri.

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