The Labeling Of Cortical Sulci Using Multidimensional Scaling

Meena Mani[1] Anuj Srivastava[2] Christian Barillot[1]

[1]INRIA/INSERM Visages U746 Project, IRISA, Rennes, France

[2]Department of Statistics, Florida State University, Tallahassee, USA

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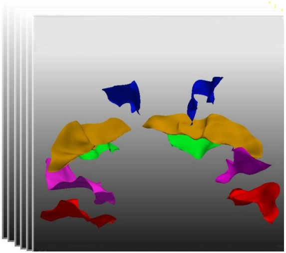
Problem Statement

To label a database of pre-segmented sulci. These share a common referential system but are not spatially normalized.



We make no assumptions about:

- predefined relationships between the sulci
- (*desideratum*) the kinds of subjects they come from

Outline

1. Background
   - The Sulcal Labeling Problem
   - The Graph Approach
   - Previous Work
   - Our Graph Approach

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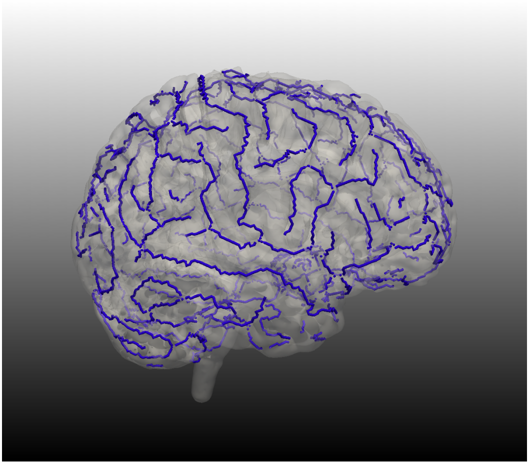
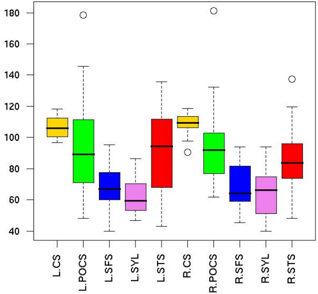
Background: Why is Sulcal Labeling Difficult?



Background: Why is Sulcal Labeling Difficult?

1. Large variation in the population
2. Individual sulci may not have unique distinguishing features

Variability in Length



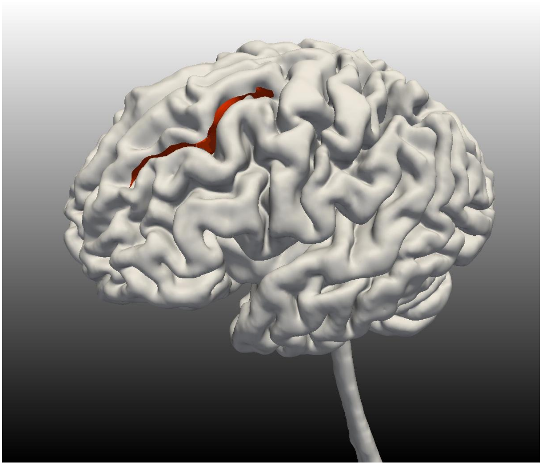
Background: The Graph Approach

Key Insight

Using a graph to model inter-sulci relationships simplifies the problem

Background: The Graph Approach

In manual annotation, neuroanatomists identify sulci by looking at their relation to other sulci



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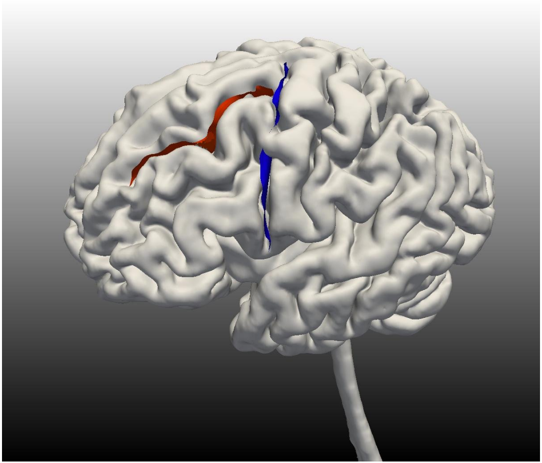

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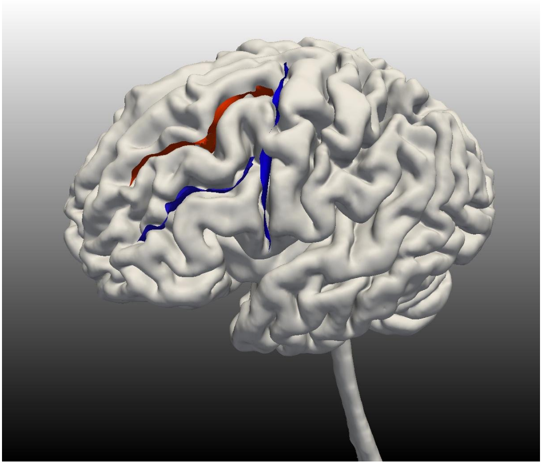


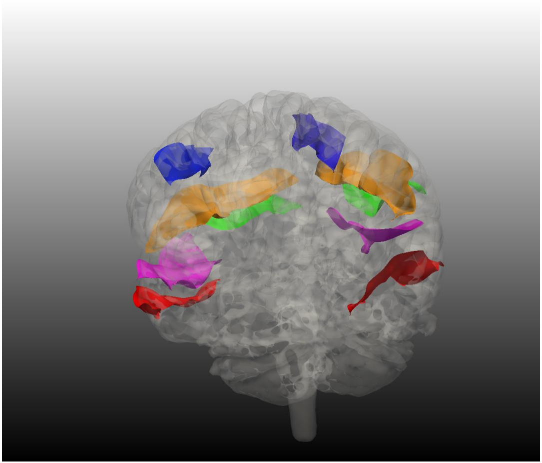
Background: The Graph Approach

Previous Approaches

- Le Goualher, G., Procyk, E., Collins, D.L., Venugopal, R., Barillot, C., Evans, A. C. Automated extraction an variability analysis of sulcal neuroanatomy. *IEEE Trans. of Medical Imaging,* 18(3): 206-217, 1999.
- Rivière, D., Mangin, J-F., Papadopoulos, D., Martinez, J-M., Frouin, V., Régis, J. Automatic recognition of cortical sulci using a congregation of neural networks. *In MICCAI, 2001.*

Background: Our Graph Approach

Construct a graph G(V,E) that assigns relationships globally



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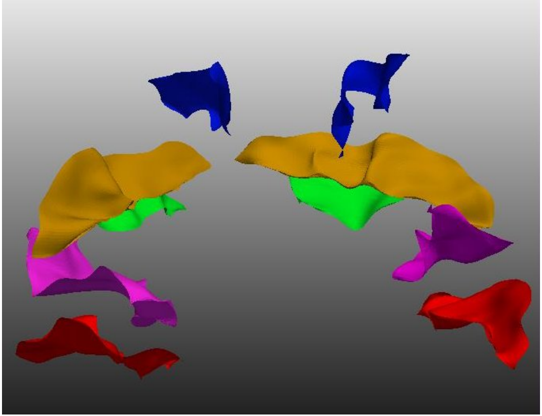

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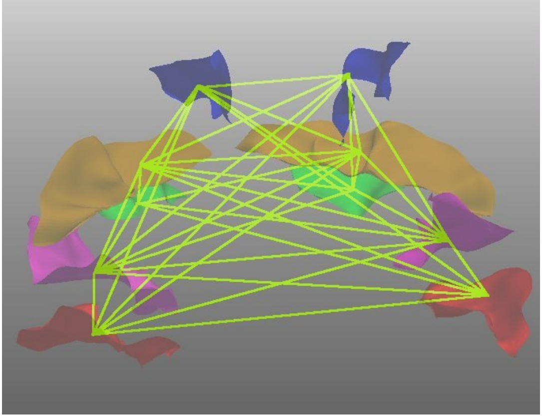

Multidimensional Scaling

Given only distance or dissimilarity data, we can assign to objects, a set of coordinates. The resulting map or embedding places objects that have similar attributes close to each other.

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Input = distance matrix
Output = coordinate matrix

Classical Multidimensional Scaling

Let $\Delta = [\delta_{ij}]$ be a distance matrix and $\Delta_2 = [\delta_{ij}^2]$
Let X be a set of coordinates

Define B s.t.

$$B = -\frac{1}{2} H \Delta_2 H$$
$$B = XX^T = \Gamma \Lambda \Gamma^T$$

Recovering X by eigen decomposition

$$X = \Gamma \Lambda^{\frac{1}{2}}$$
$$rank(X) = rank(B)$$

Classical Multidimensional Scaling

For MDS

The eigenvalue problem solves the optimization:

$$\min_{x_i \in \mathbb{R}^p} \sum_{i=2}^{n} \sum_{j=1}^{i-1} (\|x_i - x_j\| - \delta_{ij})^2$$

Classical Multidimensional Scaling

For the Out-of-Sample Extension[1]

The objective is to introduce k unlabeled sulci, $y_1, \ldots, y_k$, without disturbing an existing configuration

The *exact* solution is:

$$\min_{y \in \mathbb{R}^d} 2 \sum_{i=1}^{n} \sum_{j=1}^{k} (\|x_i - y_j\| - a_{i(n+j)})^2 + \sum_{i=1}^{k} \sum_{j=1}^{k} (\|y_i - y_j\| - a_{(n+i)(n+j)})^2$$

If we drop the second term, the resulting convex expression can be solved to give an *approximate* solution

[1] Trosset, M.W., Priebe, C.E., "The Out-of-Sample Problem for Classical Multidimensional Scaling," *Comp. Stat. & Data Anal.* **52**(10), (2008): 4635-4642

MDS can be used as a classification tool

1. Compute a distance matrix for the class averages of a set of *training sulci*
2. Generate a reference MDS map
3. Introduce unlabeled sulci to the existing map by expanding the distance matrix and minimizing an out-of-sample extension of the stress equation
4. Membership is assigned using a minimum distance classifier ($k - NN$ where $k = 1$)
5. The classification can be evaluated using leave-one-out crossvalidation (LOOCV)

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Feature Set

	Descriptors
1	Spatial Position
2	Shape
3	Orientation
4	Length
5	Mean Depth

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	Descriptors	Class Averages
1	Spatial Position	
2	Shape	Karcher mean
3	Orientation	$\mathrm{SVD}(\sum_i O_i)$
4	Length	
5	Mean Depth	

⋆*Training set represented by class averages*
⋆*Individual unlabeled sulci constitute test sulci*

Feature Set

	Descriptors	Class Averages	Distance features
1	Spatial Position		euclidean distance
2	Shape	Karcher mean	geodesic distance
3	Orientation	$\text{SVD}(\sum_i O_i)$	$\frac{\|\log(O_1 O_2^T)\|}{\sqrt(2)}$
4	Length		$\|l_1 - l_2\|$
5	Mean Depth		$\|\bar{d}_1 - \bar{d}_2\|$

⋆*Training set represented by class averages*
⋆*Individual unlabeled sulci constitute test sulci*
†*Distance matrix computed using feature distances between two sulci*

Data

18 T1-MR 3D SPGR images of healthy subjects

- sex (male)
- handedness (right)
- age (35 $\pm$ 10 years)

10 major sulci/subject

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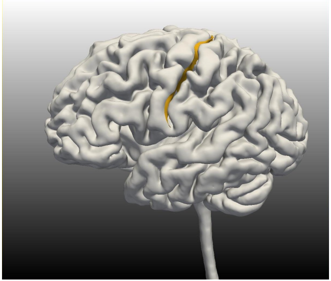
10 major sulci/subject

- left, right central sulcus



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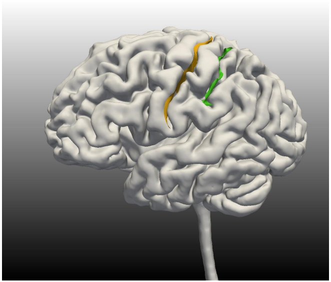
- left, right central sulcus
- left, right postcentral sulcus



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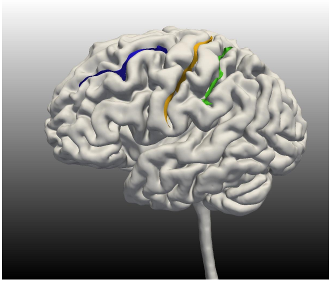
- left, right superior frontal sulcus



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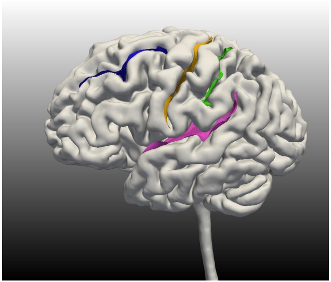
- left, right superior frontal sulcus
- left, right sylvian fissure



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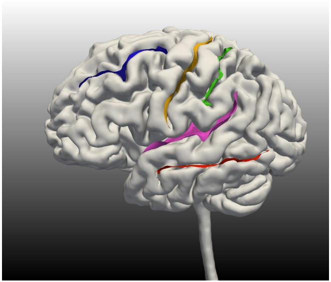

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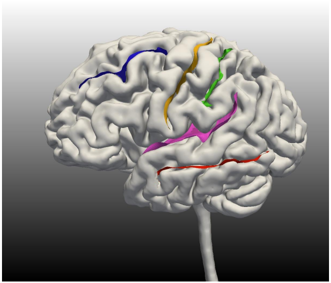
18x10 = 180 sulci



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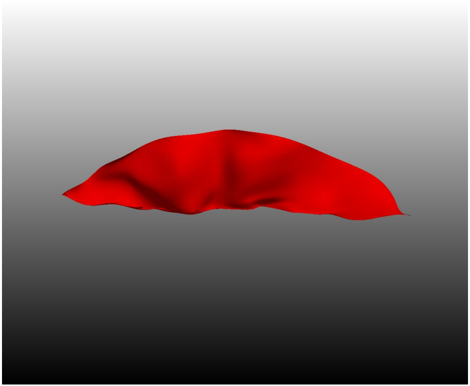
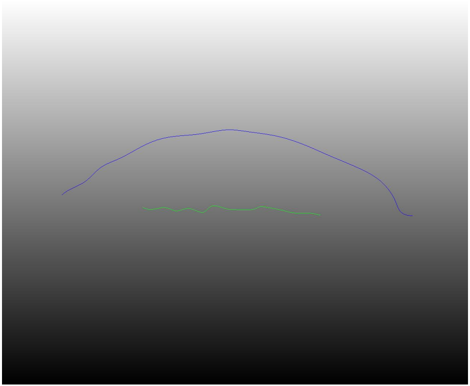


The sulci are ribbon-like surfaces

Data



The top (blue) and bottom (green) sulcal curves were used for analysis

Results

MDS Spatial Distance LOOCV (Bottom Curve)

	1	2	3	4	5	6	7	8	9	10
L.central	89	16								
L.postcentral	11	84								
L.sup. frontal			100							
L.sylvian fiss.				84	11					
L.sup. temp.				16	89					
R.central						94.5	22			
R.postcentral						5.5	78			
R.sup. front.								100		
R.sylvian fiss.									94.5	5.5
R.sup. temp.									5.5	94.5

The % of the sulci correctly identified in 18 LOO tests (blue).

The off-diagonal terms (red) give the % of false negatives.

10 classes, 18 tests/class = 180 tests. **Success rate = 163/180 = 90.6%**

Results

MDS Spatial Distance LOOCV (Top Curve)

	1	2	3	4	5	6	7	8	9	10
L.central	100	16								
L.postcentral		84								
L.sup. frontal			100							
L.sylvian fiss.				84	11					
L.sup. temp.				16	89					
R.central						94.5	22			
R.postcentral						5.5	78			
R.sup. front.								100		
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Conclusion

Advantages of the MDS spatial distance classifier

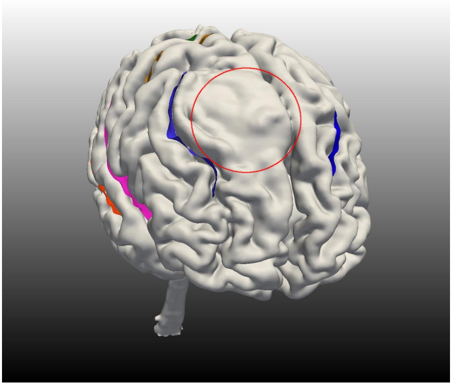
1. Quickly assign a sulcus to a small region of the left or right hemisphere
   - $\frac{180}{180}$ sulci correctly identified when classification criteria is relaxed to nearest or next-nearest neighbor
2. Classifier robust to normal population variation
   - both top and bottom sulci gave comparable results
   - superior frontal sulcus displaced by large tumor correctly identified
3. Small feature set
   - Only need $\frac{n(n-1)}{2}$ (i.e. 45 for $n = 10$) one-time distance measurements to construct a reference map
4. Easy to implement

Future Work

1. We propose a hierarchical classification scheme
   - Use the spatial distance as a front-end classifier to identify a ROI
   - Apply specialized feature classifiers in the second stage
2. Test classifier on data from brain pathologies (e.g. tumor, degenerative disease)

Classification on Tumor Data

Preliminary Results: Case 1



Large low-grade tumor ($\sim 6 \times 5 \times 5$ cm) in the right superior frontal gyrus has displaced the superior frontal sulcus

Classification on Tumor Data

Preliminary Results: Case 1

MDS Tumor Data Classification (Bottom Curve)

	1	2	3	4	5	6	7	8	9	10
L.CS	1									
L.POCS	1	0								
L.SFS			1							
L.SYL				1						
L.STS					1					
R.CS						0		1		
R.POCS						1	0			
R.SFS								1		
R.SYL									1	
R.STS										1

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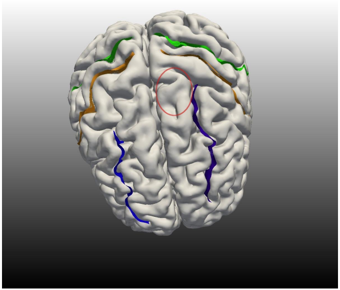
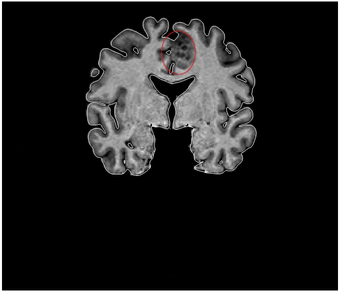
R.SYL									1	
R.STS										1

Classification on Tumor Data

Preliminary Results: Case 2





Smaller tumor ($\sim 4 \times 3 \times 3$ cm) in the left paracentral lobe

Classification on Tumor Data

Preliminary Results: Case 2

MDS Tumor Data Classification (Bottom Curve)

	1	2	3	4	5	6	7	8	9	10
L.CS	1									
L.POCS		1								
L.SFS			1							
L.SYL				1						
L.STS					1					
R.CS						1				
R.POCS						1	0			
R.SFS								1		
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Classification on Tumor Data

Preliminary Results: Case 2

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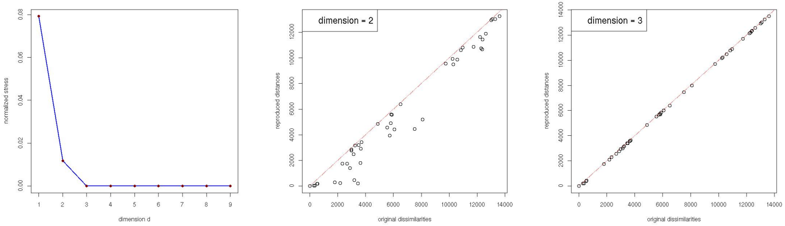
R.SYL									1	
R.STS										1

Questions

Evaluating Dimensionality, Assessing Fit

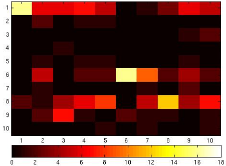


(a) Scree plot (b) Shepard: 2D (c) Shepard: 3D

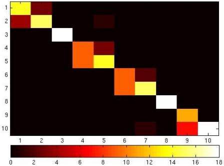
Figure: The scree plot shows that 3 dimensions is optimal for the MDS map. The Shepard plot for 2D data shows more spread than the corresponding 3D plot.

MDS Classification Results

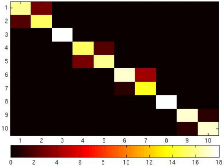
Shape and Position



(a) Shape



(b) Shape + Position

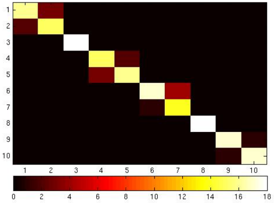


(c) Position

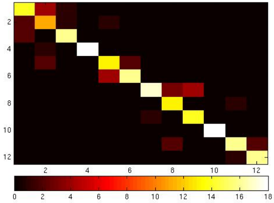
Figure: The shape distance results improve considerably when the shape & spatial distances are combined. The spatial distance alone gives the best perfomance.

MDS Classification Results

10 vs 12 Classes



(a) 10 sulcal classes



(b) 12 sulcal classes

Figure: The results for the spatial distance deteriorated when the two precentral sulci were added, increasing the number of classes to 12. The precentral sulcus was sometimes miscategorized as the adjacent sylvian fissure, the central or superior frontal sulcus.

Elastic Shape Formalism for Sulcal Curves

Pre-shape Space $\mathcal{B}$

The square-root velocity function:

$$q(t) = \frac{\dot{\beta}(t)}{\sqrt{\|\dot{\beta}(t)\|}} , \quad t \in [0, 1]$$

Compute the geodesic paths between curves using:

$$\psi(t) = \frac{1}{\sin(\theta)} [\sin(\theta - t)q_1 + \sin(t)q_2]$$

The geodesic distance, denoted by $d_c(q_1, q_2)$, is:

$$\theta = \cos^{-1}(\langle q_1, q_2 \rangle)$$

Shape Space $\mathcal{S}$

We define the shape space as:

$$\mathcal{S} = \mathcal{B}/(\Gamma \times SO(3))$$

The geodesic distance between two orbits $[q_1]$ and $[q_2]$:

$$d_s([q_1], [q_2]) = \min_{\gamma \in \Gamma, O \in SO(3)} d_c(q_1, \sqrt{\dot{\gamma}} O q_2(\gamma))$$

The Karcher mean is:

$$\bar{\mu}_n = \underset{[q] \in \mathcal{S}}{\operatorname{argmin}} \sum_{i=1}^{n} d_s([q], [q_i])^2$$