

Supervised Labeling of Brain Sulci using Multidimensional Scaling Meena Mani Visages Lab, IRISA/INRIA, Rennes, France





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
- semantic information
- (desideratum) the kinds of subjects they come from



Feature Set

Descriptors	Class Averages	Distance features
1 Spatial Position [†]		euclidean distance
2 Shape [‡]	Karcher mean	geodesic distance
3 Orientation	$SVD(\sum_i O_i)$	$\frac{\ \log(O_1O_2^T)\ }{\sqrt{(2)}}$
4 Length		$ I_1 - I_2 $
5 Mean Depth		$ ar{d}_1 - ar{d}_2 $

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

[†]3 different position distances evaluated-midpoint, mean closest point, median closest point ‡joint work with Anuj Srivastava, Department of Statistics, Florida State University

The Sulcal Labeling Problem

1. Large feature variation in the population (feature selection problem) 2. Convolutions vary from subject to subject and across hemispheres (template) matching problem)

Variability in Length

Complexity of Patterns





Expert Annotation–The Graph Approach

In manual annotation, neuroanatomists identify



Results

18 T1-MR 3D SPGR images of healthy subjects

- ► sex (male)
- handedness (right)
- ▶ age $(35 \pm 10 \text{ years})$
- 10 major sulci/subject
- ► left, right central sulcus
- Ieft, right postcentral sulcus
- Ieft, right superior frontal sulcus
- left, right sylvian fissure
- Ieft, right superior temporal sulcus

18x10 = 180 sulci



MDS Spatial Position Distance LOOCV

	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

sulci by looking at their relation to other sulci

Classical Multidimensional Scaling

MDS gives a physical map with which we can reproduce the structural relationships between sulci. The eigenvalue problem solves the optimization:



For the Out-of-Sample Extension[†]:

The objective is to introduce k unlabeled sulci, y_1, \ldots, y_k , without disturbing an existing configuration. The exact solution is:

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

If we drop the second term, the resulting convex expression can be solved numerically to give an approximate out-of-sample embedding.

[†]Trosset, M.W., Priebe, C.E., "The Out-of-Sample Problem for Classical Multidimensional Scaling," Comp. Stat. & Data Anal. 52(10), (200 8): 4635-4642.

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%

Labeling Tumor Data



The labeling error for 4 patients in the unaffected cortical regions is the same as for the healthy subjects. In the affected regions(shaded boxes), the sulci are correctly labeled in 3 cases. The sulcus does not exist in the last case.

Classification with MDS

- 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 obtain an out-of-sample embedding
- 4. Membership is assigned using the nearest-neighbor criterion 5. The classification can be evaluated using leave-one-out crossvalidation (LOOCV)

Advantages of the MDS spatial distance classifier

- 1. Quickly assign a sulcus to a small region of the left or right hemisphere ¹⁷⁹/₁₈₀ sulci correctly identified when classification criteria is relaxed to nearest or next-nearest neighbor
- 2. Classifier robust to normal population variation
 - b do not need to register the sulci
 - both top and bottom sulci gave comparable results
- can identify sulci displaced by large tumors (use as a general purpose labeling tool) 3. Fast, lightweight
 - CMDS and NN search performed on group averaged data
 - 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 using off-the-shelf algorithms

Machine Learning Summer School, Chicago, 2009

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