

A Surface-based Approach for Classification of 3D Neuroanatomic Structures

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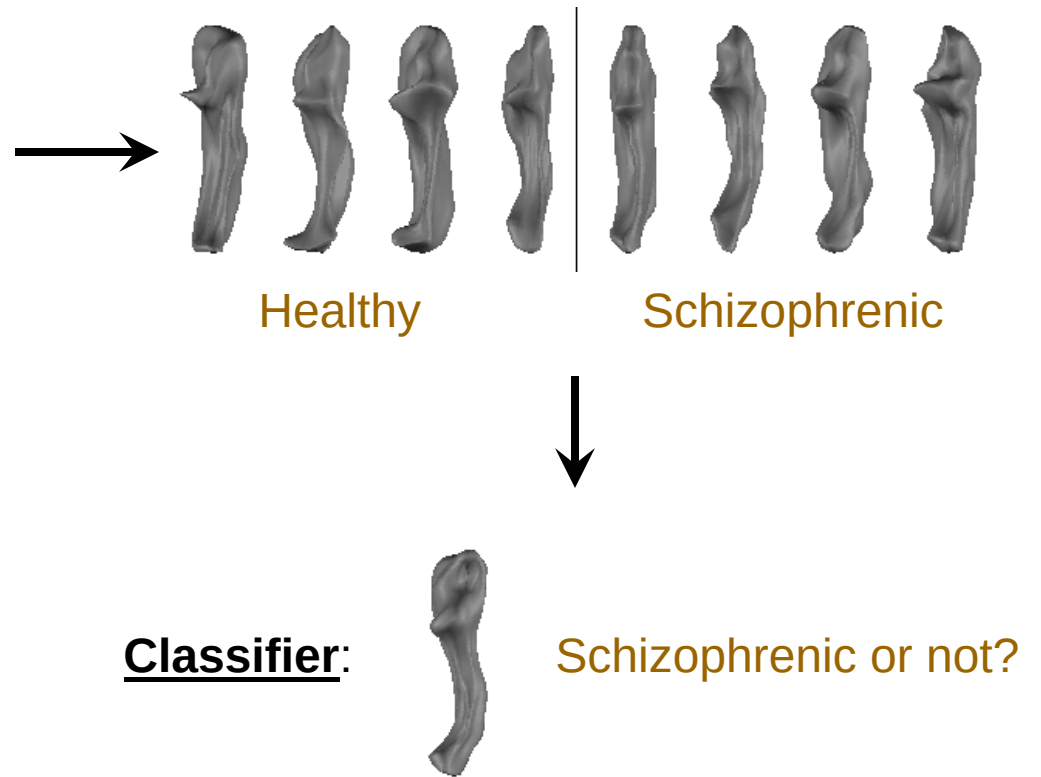
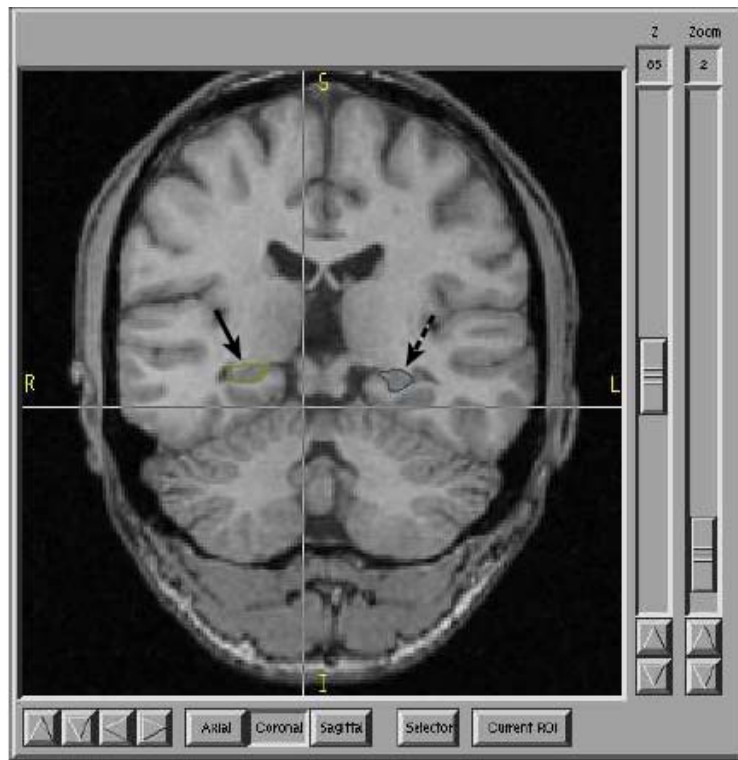
Outline

- [Introduction](#)
 - Surface Modeling
 - Topology correction
 - Spherical parameterization
 - SPHARM expansion
 - SPHARM registration
 - Pattern Classification
 - Dimensionality reduction
 - Feature selection
 - Classification
 - Results and visualization
 - Summary
-

Shape?

- I. L. Dryden and K. V. Mardia. *Statistical Shape Analysis*. J. Wiley, New York, 1998.
 - All the geometrical information that remains when location, scale, and rotational effects are filtered out from an object.
-

Hippocampal Shape in Schizophrenia



Related Work: Hippocampal Shape Classification

	Shape Representation	Classification	Cross-validation Result
Csernasky et al. (98,02)	Deformation fields	LDA	80%, 74%
Timoner, Golland et al. (00,02)	Distance transforms, displacement fields	SVM	77%, 87%
Saykin et al. (03)	Binary images	PCA	96%
Davies et al. (03)	SPHARM + MDL	LDA	*
Gerig et al. (01)	SPHARM => asymmetry + volume	SVM	87%

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Object Surface

- Surface of a voxel volume (i.e., a binary image)



Source: Kelemen TMI 18(10)

- Spherical topology: correction if necessary
 - Simple cases
 - Bad edge connectivity
 - Bad vertex connectivity: two cases
 - 3D holes
-

Topology Correction

- Simple cases
 - Disconnected components
 - Holes inside the object
- Bad edge connectivity
- Bad vertex connectivity
- 3D holes

Z. Aktouf et al. / Pattern Recognition Letters 23 (2002) 523–531

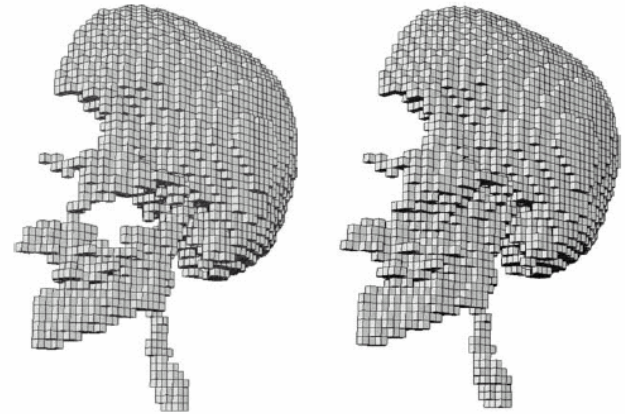
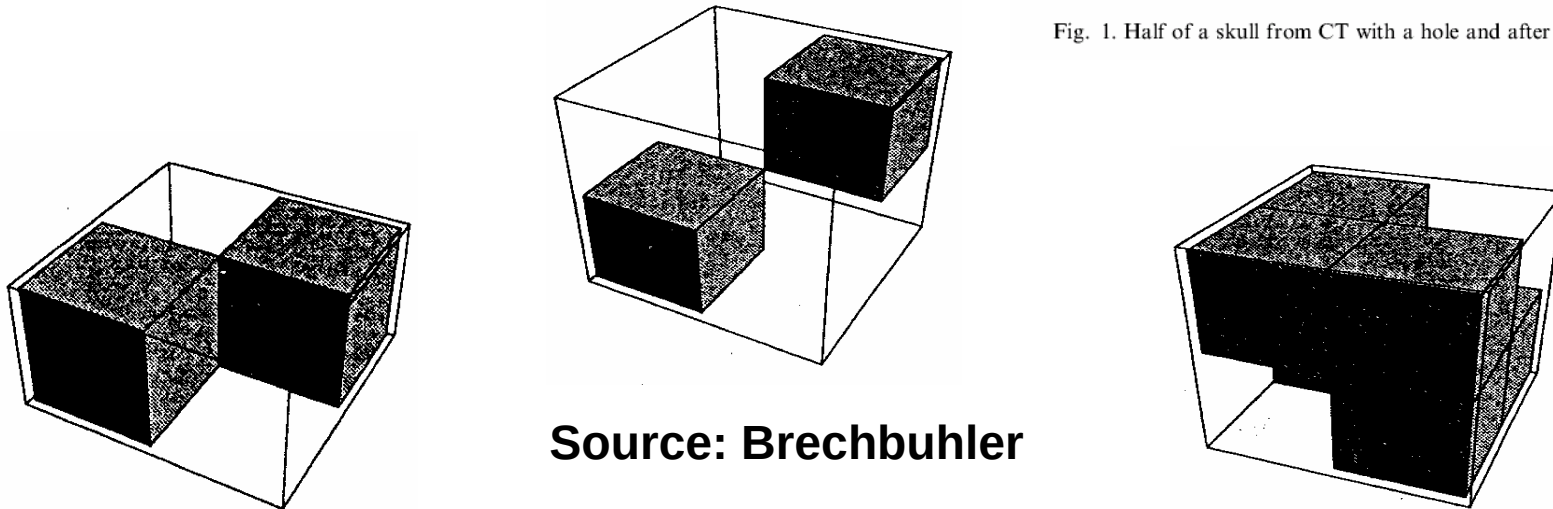
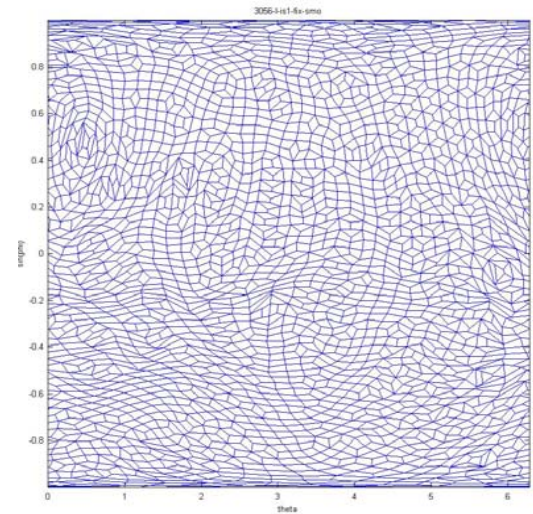
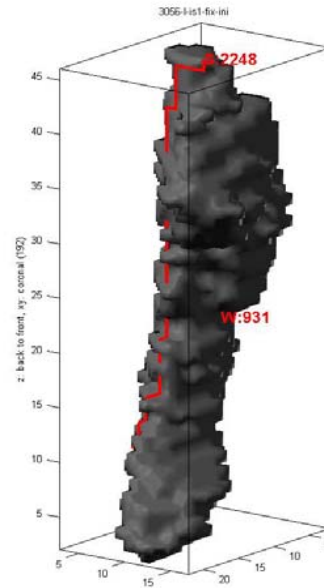
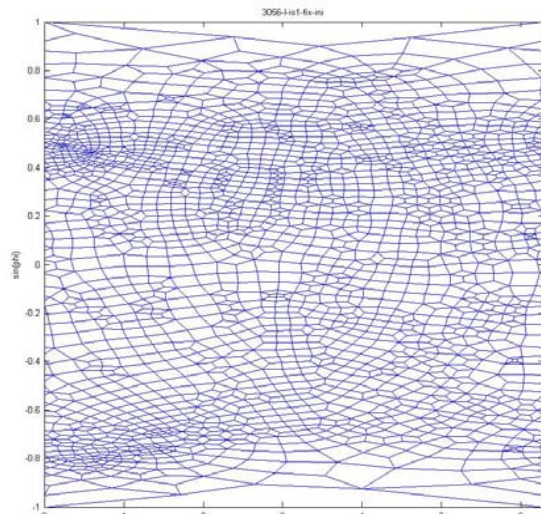


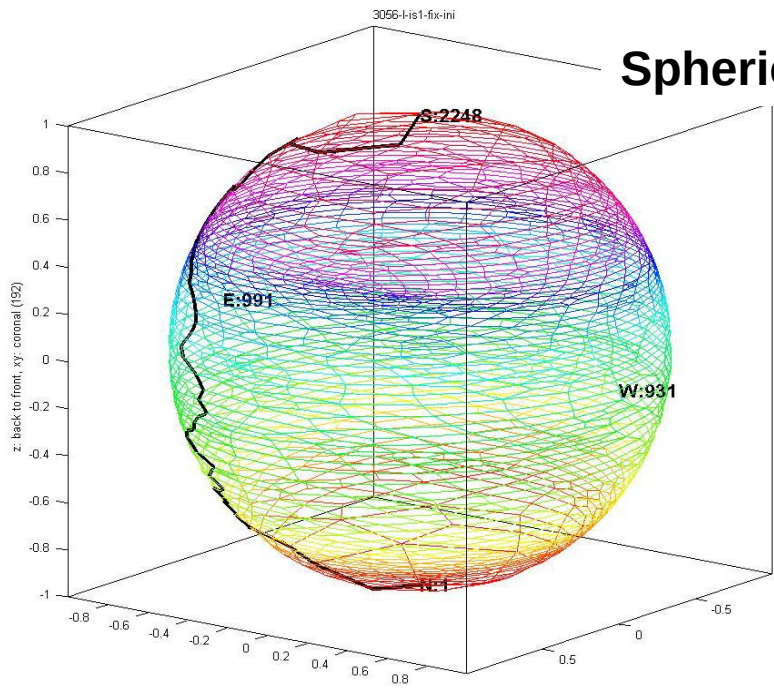
Fig. 1. Half of a skull from CT with a hole and after closing the hole.



Source: Brechbuhler

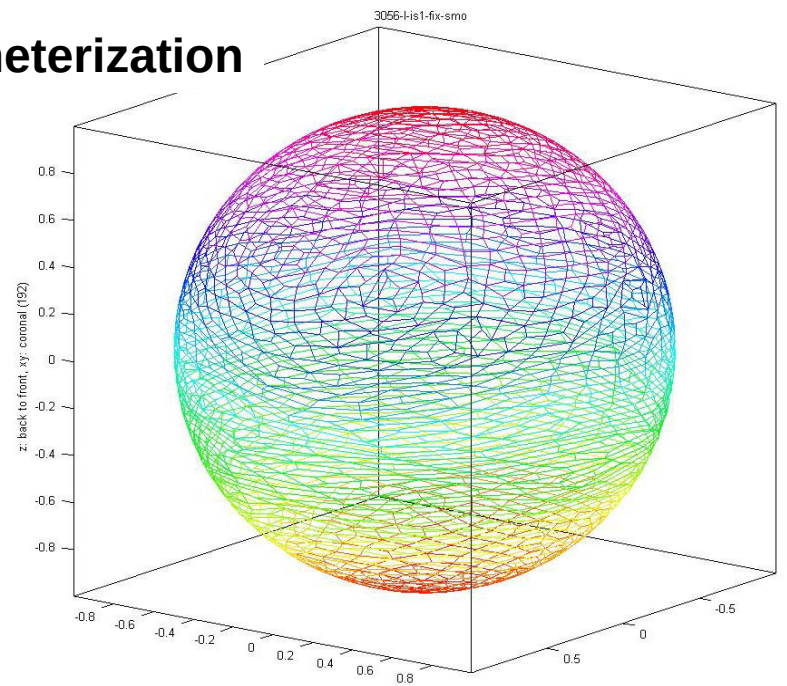


Spherical Parameterization



y: top to bottom, xz: axial

x: left to right, yz: sagittal



y: top to bottom, xz: axial

x: left to right, yz: sagittal

Harmonic Mapping

- Select two vertices for poles
 - With maximal and minimal z coordinates
- Latitude from diffusion
 - Grow smoothly from 0 at north to π at south

$$\nabla^2 \theta = 0 \quad (\text{except at the poles})$$

$$\theta_{north} = 0$$

$$\theta_{south} = \pi$$

- Longitude from diffusion
-

Smoothing by Optimization

$$\text{minimize } F(\underline{x}) = \left(-\frac{1}{2}\right) \cdot \sum_{\substack{i \in \text{All the} \\ \text{Vertices}}} \sum_{\substack{j \in \text{Direct Neighbours} \\ \text{of vertex } i}} \{x_i \ y_i \ z_i\} \cdot \{x_j \ y_j \ z_j\}$$

$$\text{subject to} \quad \text{Area} \left(\begin{array}{c} \text{Spherical} \\ \text{Quadrilateral} \end{array} \right) - \frac{4\pi}{\text{Number of Faces}} = 0,$$

for all spherical Quadrilaterals

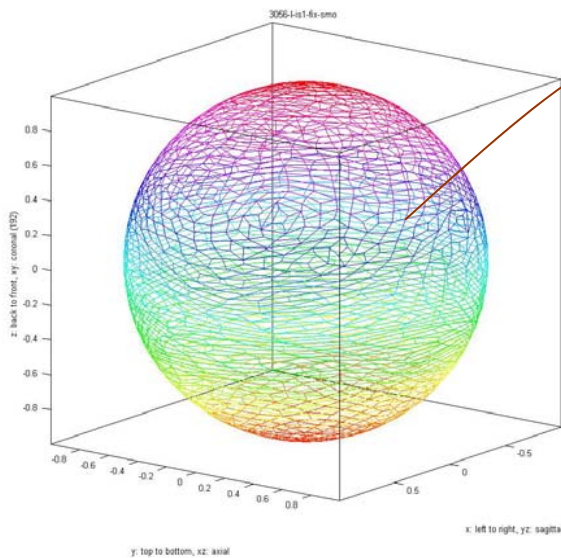
$$x^2 + y^2 + z^2 - 1 = 0, \text{ for all vertices } (x, y, z)$$

$$\text{and} \quad \sin a_i = 0 \text{ for } a_i \text{ spherical angle with } \sin a_i \leq 0$$

SPHARM Surfaces

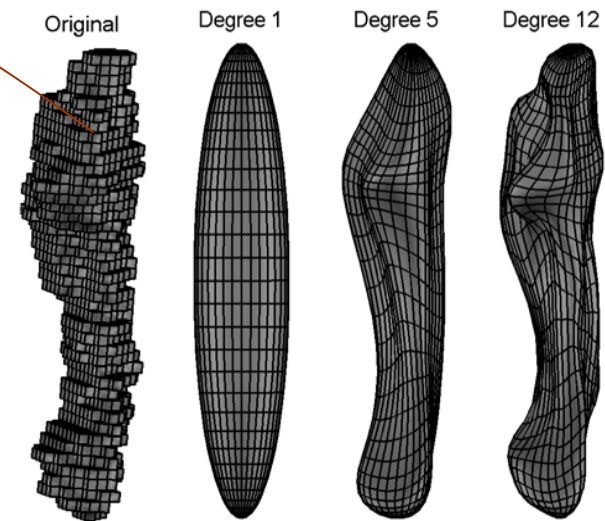
$$\mathbf{v}(\theta, \phi) = \sum_{l=0}^{\infty} \sum_{m=-l}^l \mathbf{c}_l^m Y_l^m(\theta, \phi)$$

$$\mathbf{v}(\theta, \phi) = \begin{pmatrix} x(\theta, \phi) \\ y(\theta, \phi) \\ z(\theta, \phi) \end{pmatrix} \quad \mathbf{c}_l^m = \begin{pmatrix} c_{xl}^m \\ c_{yl}^m \\ c_{zl}^m \end{pmatrix}$$



$$(\theta, \phi) \leftrightarrow (x, y, z)$$

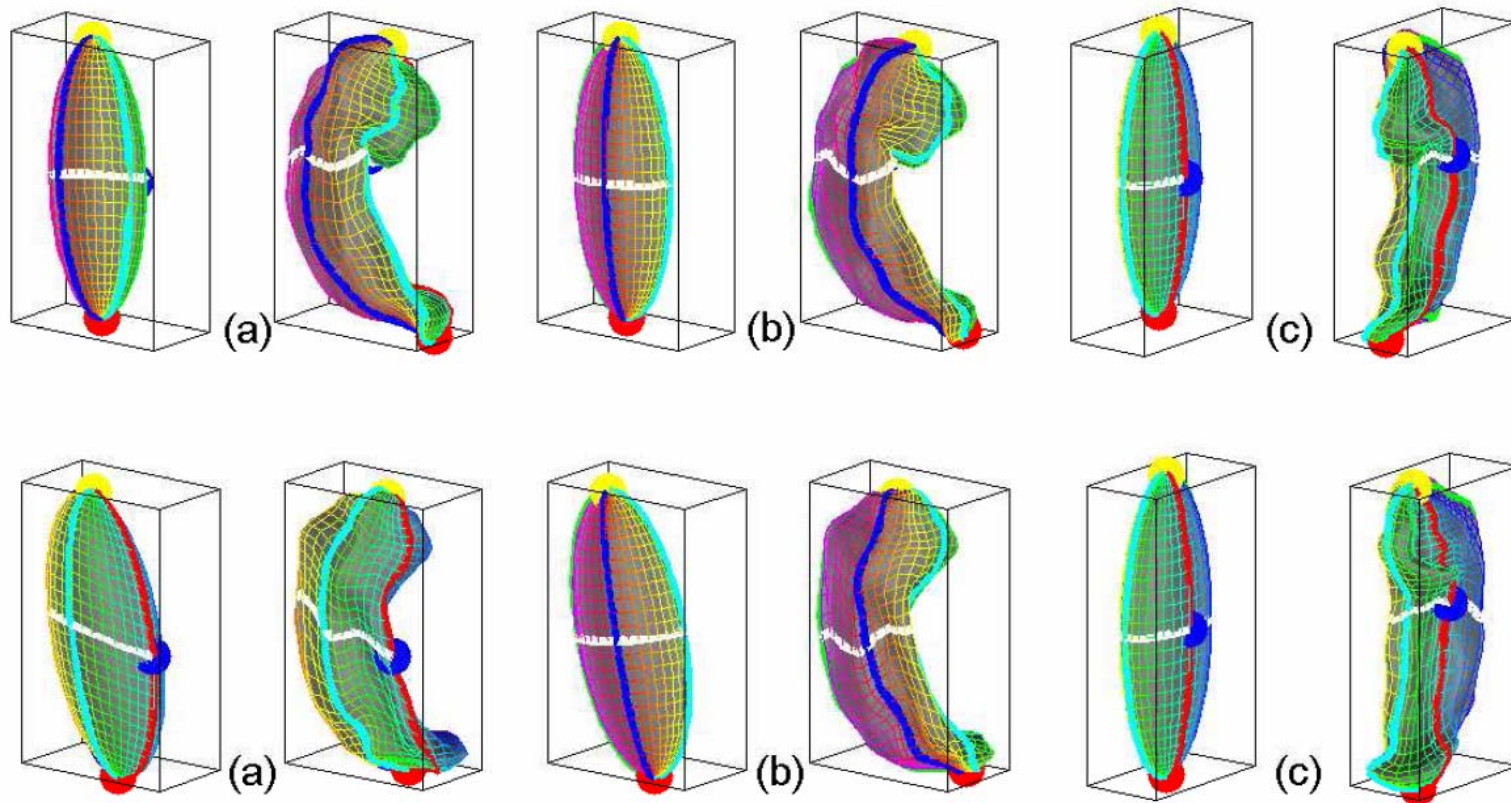
Area-preserving
mapping



SPHARM Registration

- Scaling
 - Dividing all descriptors by the scaling factor (SF)
 - Translation
 - Ignoring the degree 0 SPHARM term.
 - Rotation: in the parameter space
 - Dateline ($\phi=0$) crosses the equator ($\theta=\pi/2$) at the positive end of the shortest main axis
 - South pole ($\theta=\pi$) is at the positive end of the longest main axis
 - Rotation: in the object space
 - The ellipsoid is rotated to make its main axes coincide with the coordinate axes, putting the shortest axis along x and longest along z
-

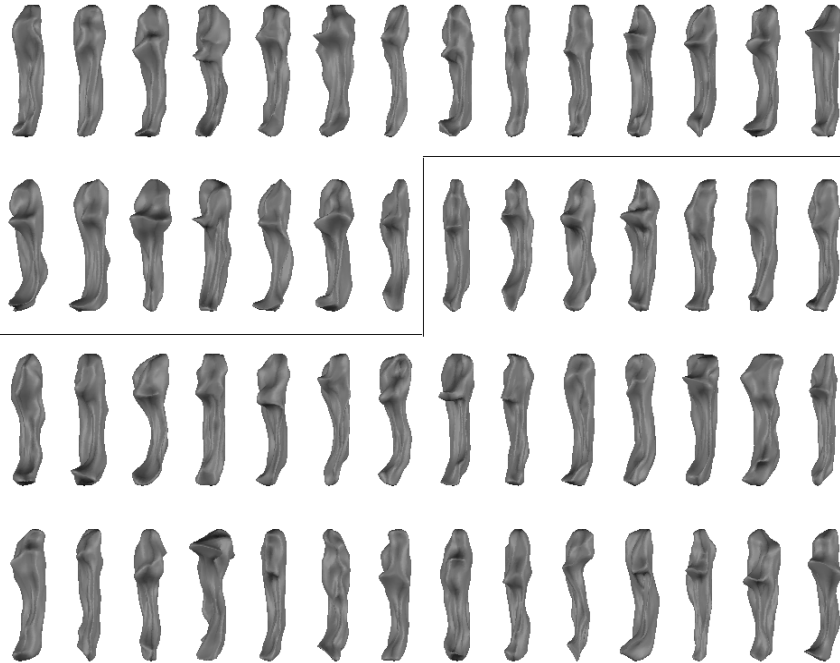
SPHARM Registration



(a) Original objects (b) aligned parameterizations (c) aligned objects
Works only if FOE is a real ellipsoid

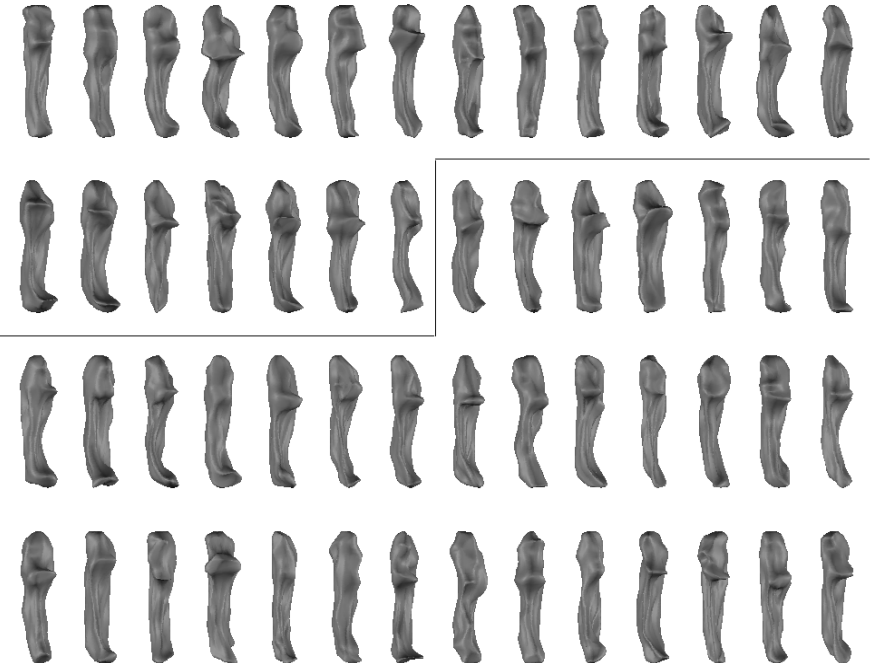
SPHARM Registration

Left Controls



Left Patients

Right Controls



Right Patients

S_{all}: 35 schizophrenics, 21 controls

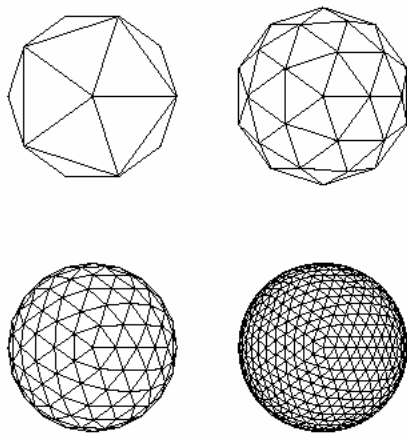
S_{rh}m: 25 schizophrenics, 14 controls

Outline

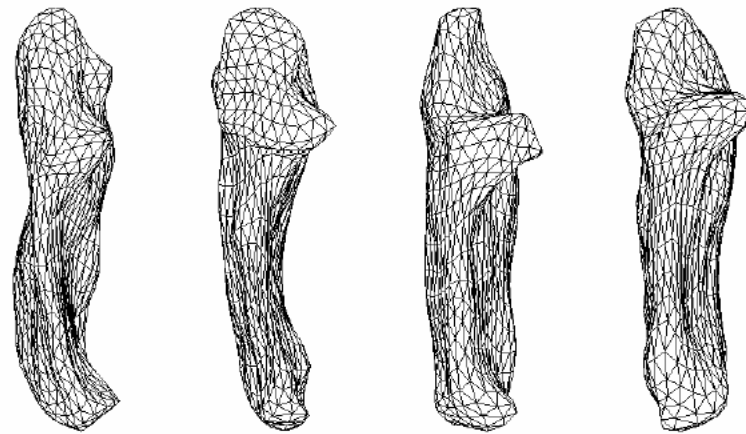
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Dual Landmark Representation

- Uniform sampling for landmarks



(a) Icosahedron subdivisions



(b) Sampled hippocampal surfaces

$$\mathbf{v}(\theta, \phi) = \sum_{l=0}^{\infty} \sum_{m=-l}^l \mathbf{c}_l^m Y_l^m(\theta, \phi)$$

$$\mathbf{x} = (x_1, \dots, x_n, y_1, \dots, y_n, z_1, \dots, z_n)^T$$

Dimensionality Reduction: Point Distribution Model

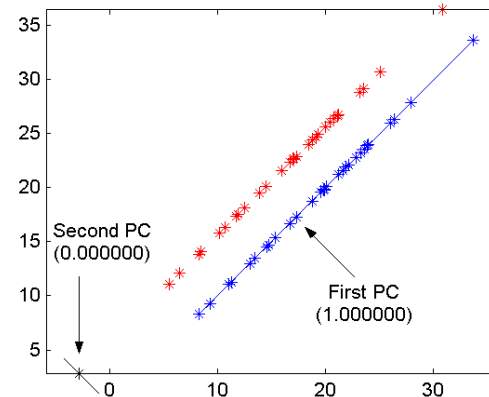
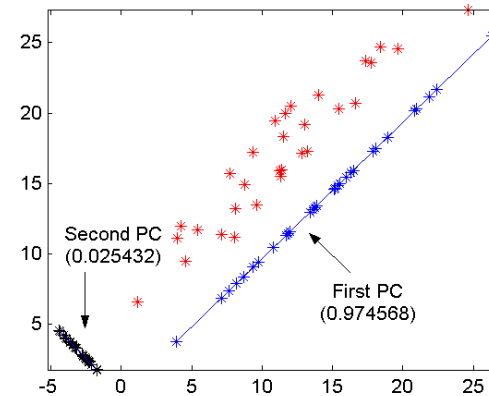
- Principal component analysis on landmarks

$$\Sigma = \frac{1}{N-1} \sum_{i=1}^N (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T,$$

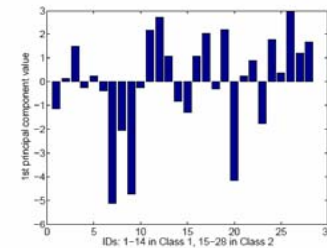
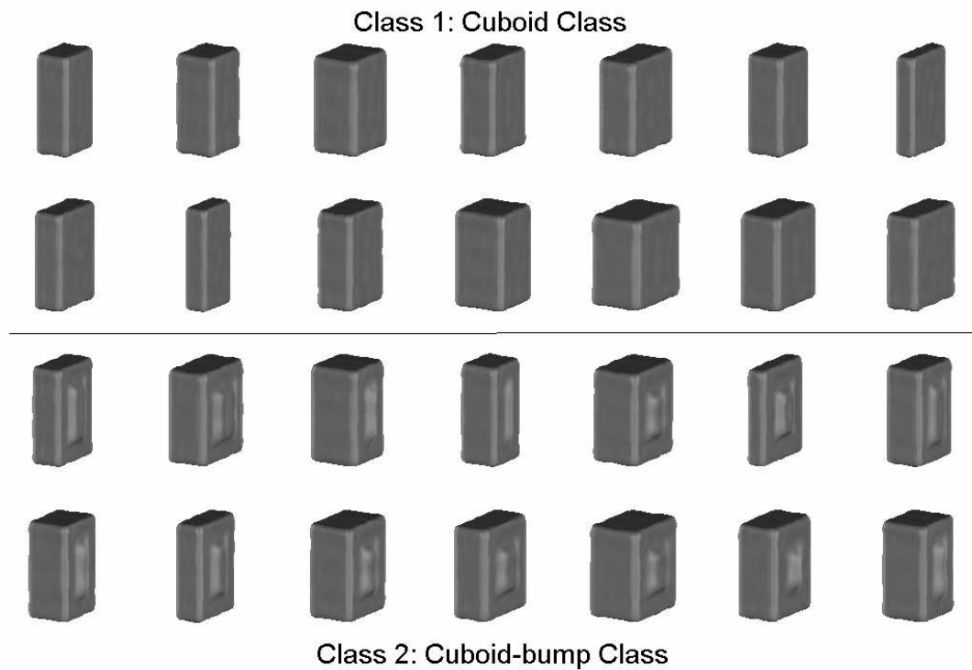
$$\Sigma \mathbf{P} = \mathbf{P} \mathbf{D},$$

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P} \mathbf{b}, \quad \mathbf{b} = \mathbf{P}^T (\mathbf{x} - \bar{\mathbf{x}}).$$

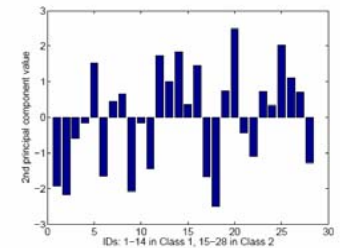
- 1926 landmark elements => 55 features



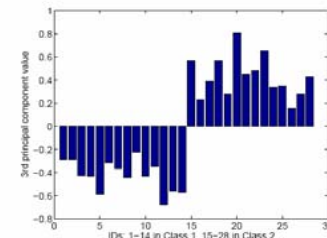
Feature Selection



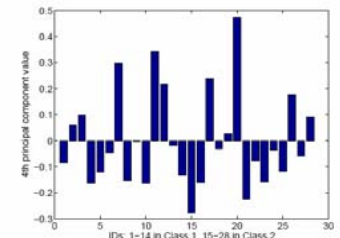
(a) First principal component



(b) Second principal component



(c) Third principal component

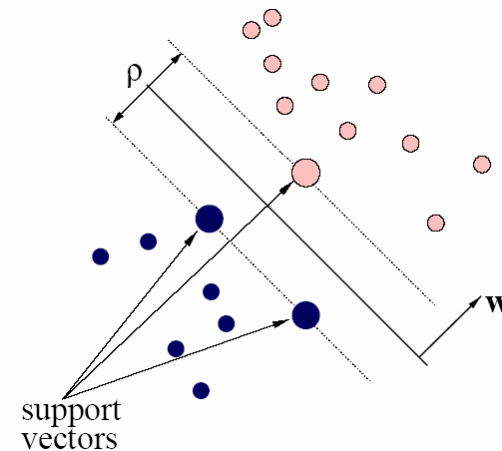
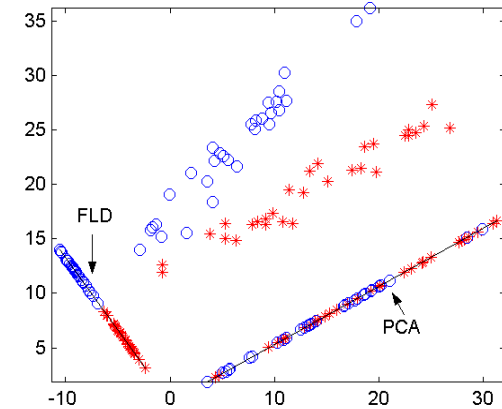


(d) Fourth principal component

- PCV: variance accounted for
- PCTt: p-value from t-test on leave-one-out training set

Classification

- Feature Selection
 - PCTt: reordering of PC using t-test
 - Consider the first N features
- Classifiers
 - Fisher's linear discriminant (FLD)
 - Linear support vector machine (SVM)
- Leave-one-out cross-validation



Best Results

	Left of S_{all}	Right of S_{all}	Left of S_{rhm}	Right of S_{rhm}
FLD-BM	93%, 19	79%, 2	82%, 16	82%, 17
FLD-1NN	89%, 17	79%, 11	79%, 12	87%, 17
FLD-3NN	89%, 19	79%, 2	82%, 18	87%, 17
FLD-5NN	89%, 19	79%, 2	82%, 16	87%, 17
FLD-7NN	91%, 19	79%, 14	82%, 18	90%, 17
FLD-NM	91%, 19	79%, 14	82%, 19	90%, 17
SVM-C1	80%, 19	82%, 13	69%, 12	85%, 17
SVM-C10	93%, 19	82%, 13	77%, 14	90%, 17
SVM-C100	91%, 17	82%, 15	77%, 14	90%, 17

(Cross-validation accuracy, Number of features used)

Shape and Volume

Left Hippocampi

	NV	V0	V1	V2
FLD-BM	93%, 19	93%, 19	93%, 19	93%, 19
FLD-1NN	89%, 17	89%, 19	89%, 19	88%, 19
FLD-3NN	89%, 19	91%, 19	89%, 19	89%, 19
FLD-5NN	89%, 19	89%, 19	89%, 19	89%, 19
FLD-7NN	91%, 19	91%, 19	91%, 19	91%, 19
FLD-NM	91%, 19	89%, 19	91%, 19	91%, 19
SVM-C1	80%, 19	80%, 11	75%, 10	77%, 19
SVM-C10	93%, 19	95%, 19	91%, 19	89%, 17
SVM-C100	91%, 17	95%, 19	89%, 19	89%, 18

Right Hippocampi

	NV	V0	V1	V2
FLD-BM	79%, 2	80%, 13	79%, 13	79%, 13
FLD-1NN	79%, 11	75%, 14	75%, 14	75%, 14
FLD-3NN	79%, 2	79%, 13	77%, 14	77%, 13
FLD-5NN	79%, 2	77%, 13	77%, 13	77%, 13
FLD-7NN	79%, 14	77%, 13	77%, 13	77%, 13
FLD-NM	79%, 14	79%, 13	79%, 13	79%, 13
SVM-C1	82%, 13	82%, 13	82%, 10	82%, 10
SVM-C10	82%, 13	82%, 13	80%, 14	80%, 14
SVM-C100	82%, 15	84%, 15	82%, 15	82%, 15

Whole
Set

Right
Handed
Males

	NV	V0	V1	V2
FLD-BM	82%, 16	82%, 22	85%, 17	85%, 18
FLD-1NN	79%, 12	79%, 12	82%, 22	82%, 21
FLD-3NN	82%, 18	85%, 22	82%, 16	82%, 22
FLD-5NN	82%, 16	85%, 22	82%, 16	85%, 22
FLD-7NN	82%, 18	82%, 22	85%, 22	85%, 22
FLD-NM	82%, 19	82%, 24	85%, 22	85%, 18
SVM-C1	69%, 12	77%, 30	74%, 15	74%, 15
SVM-C10	77%, 14	79%, 30	85%, 19	77%, 19
SVM-C100	77%, 14	79%, 30	85%, 19	77%, 19

	NV	V0	V1	V2
FLD-BM	82%, 17	85%, 17	82%, 17	79%, 17
FLD-1NN	87%, 17	82%, 16	79%, 17	82%, 17
FLD-3NN	87%, 17	82%, 17	82%, 17	82%, 17
FLD-5NN	87%, 17	87%, 17	82%, 17	82%, 17
FLD-7NN	90%, 17	87%, 17	82%, 17	82%, 17
FLD-NM	90%, 17	87%, 17	82%, 16	82%, 16
SVM-C1	85%, 17	79%, 17	85%, 17	82%, 17
SVM-C10	90%, 17	85%, 16	90%, 17	90%, 17
SVM-C100	90%, 17	85%, 16	90%, 17	90%, 17

NV: no volume

V0: absolute volume

V1: volume scaled by total brain tissue volume

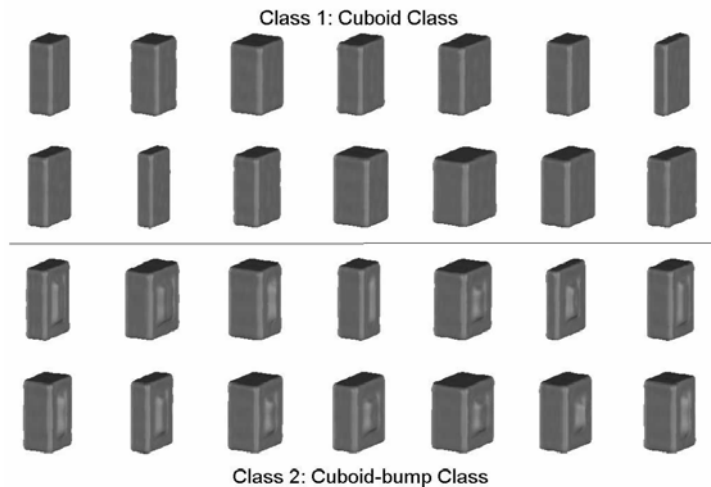
V2: volume scaled by intracranial volume

Discriminative Patterns

- PCA + FLD

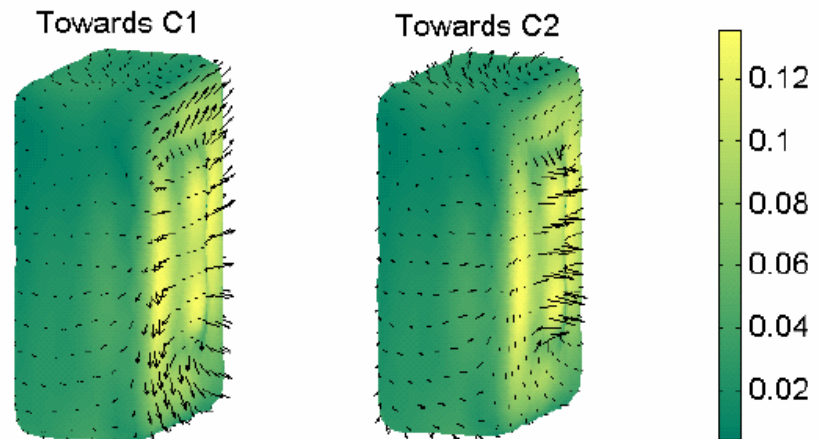
$$v = \mathbf{x}_\delta^T * B_{pca} * B_{fld} = \mathbf{x}_\delta^T * W,$$

$$\mathbf{x}_\delta = \mathbf{X} - \bar{\mathbf{X}}$$



- Contribution to v by landmark l

$$C(l) = \mathbf{x}_\delta(l)^T * W(l)$$



Discriminative Patterns

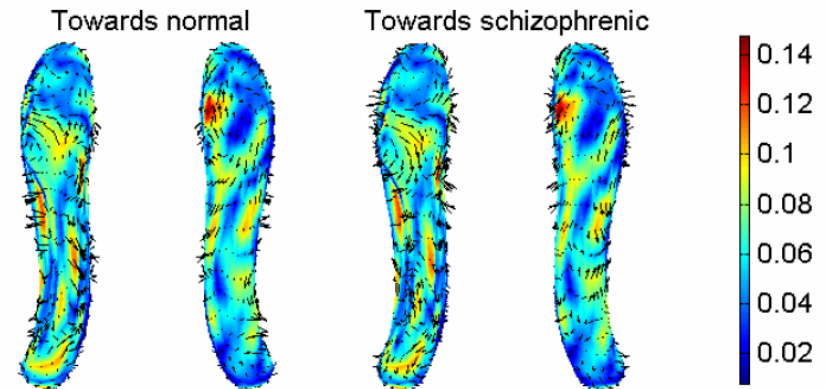
- PCA + FLD

$$v = \mathbf{x}_\delta^T * B_{pca} * B_{fld} = \mathbf{x}_\delta^T * W,$$

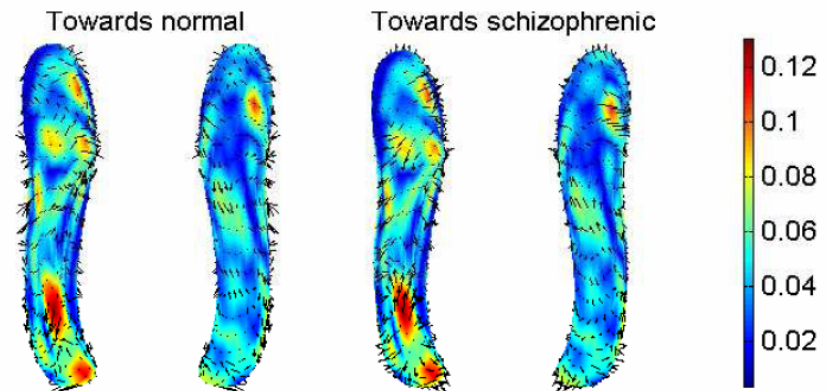
$$\mathbf{x}_\delta = \mathbf{x} - \bar{\mathbf{x}}$$

- Contribution to v by landmark l

$$C(l) = \mathbf{x}_\delta(l)^T * W(l)$$



(a) Discriminative patterns for S_{all}^{left}



(b) Discriminative patterns for S_{all}^{right}

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