Three-dimensional Model-based Segmentation of Brain MRI

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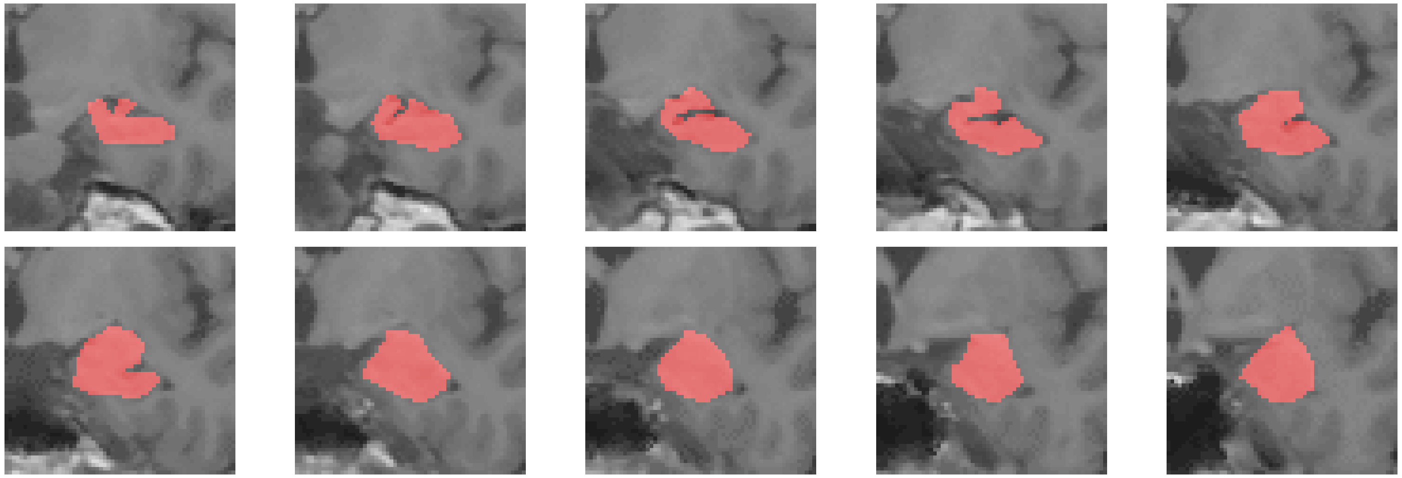
Topics:

- Manual Segmentation
- Automatic Segmentation (Related Work)
- Building 3-D Organ Models
- Computing Shape Statistics
- Modeling Gray-Level Environment
- Elastic Matching Algorithm
- Results & Validation

Where is segmentation needed?

- Computer Assisted Neurosurgery
- Radiotherapy Planning
- Understanding of Brain Diseases
- Morphometry

Manual 3-D Segmentation



Advantages: Interactive

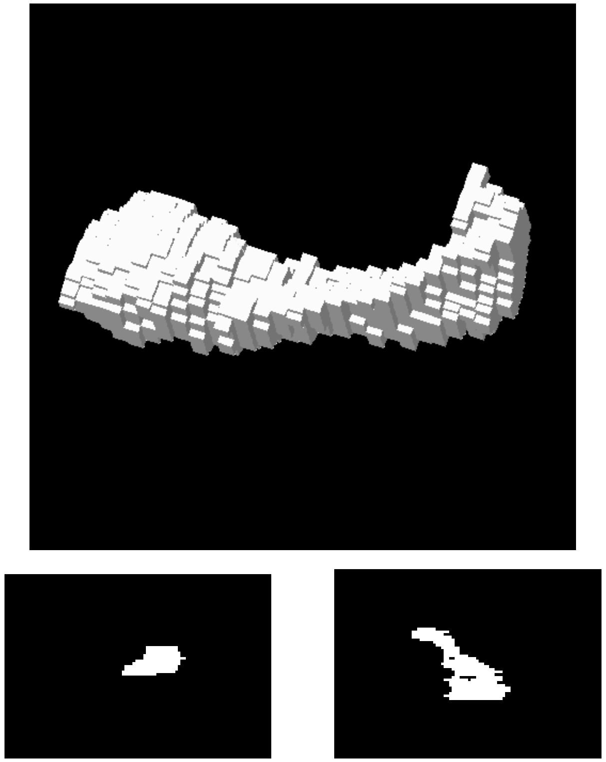
Disadvantages:
- Inaccurate
- Poor Reproducibility
- 3-D from 2-D Slices
- Slow and Tedious

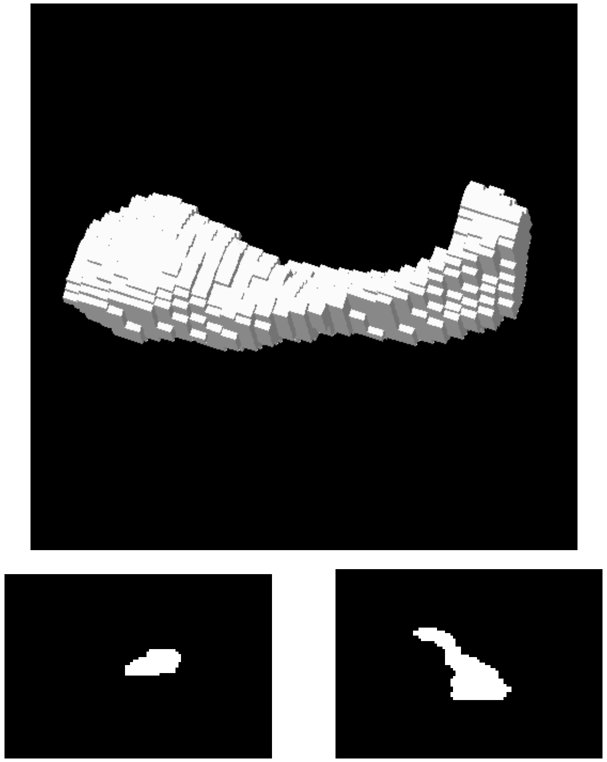
Automatic Segmentation: Related Work

- L.H. Staib & J.S. Duncan: 3D fourier organ models, region and gradient based segmentation.
- T.F. Cootes & C.J. Taylor: 2D statistical organ models, modelling gray level appearance, least-squares based segmentation.
- G. Szekely et al.: 2D statistical organ models, gradient based segmentation
- B. Vemuri et al.: Multiresolution stochastic hybrid shape models

Model Building

Segmented MRI data from R. Kikinis/M.Shenton, Harvard Medical School, BWH





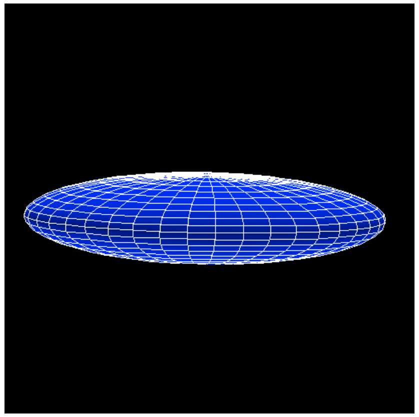
Parametrization 1

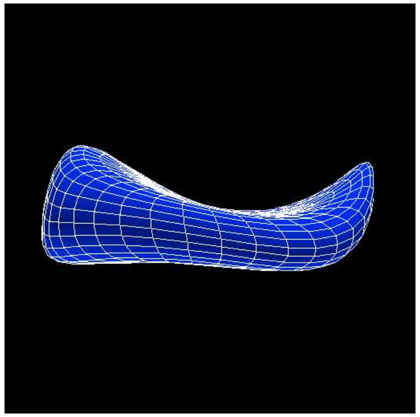
co-ordinate functions: $\mathbf{r}(\theta, \phi) = \begin{pmatrix} x(\theta, \phi) \\ y(\theta, \phi) \\ z(\theta, \phi) \end{pmatrix}$

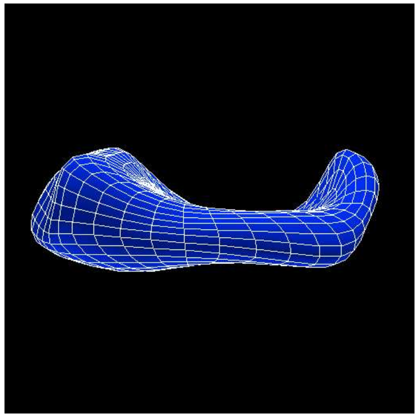
series of orthogonal basis functions: $\mathbf{r}(\theta, \phi) = \sum_{k=0}^{K} \sum_{m=-k}^{k} \mathbf{c}_k^m Y_k^m(\theta, \phi)$

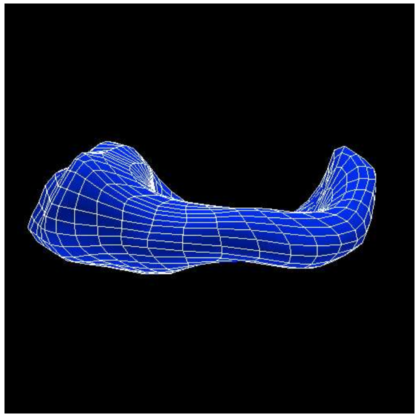
descriptors: $\mathbf{c}_k^m = \begin{pmatrix} c_{x}{}_k^m \\ c_{y}{}_k^m \\ c_{z}{}_k^m \end{pmatrix}$

Parametrization 2

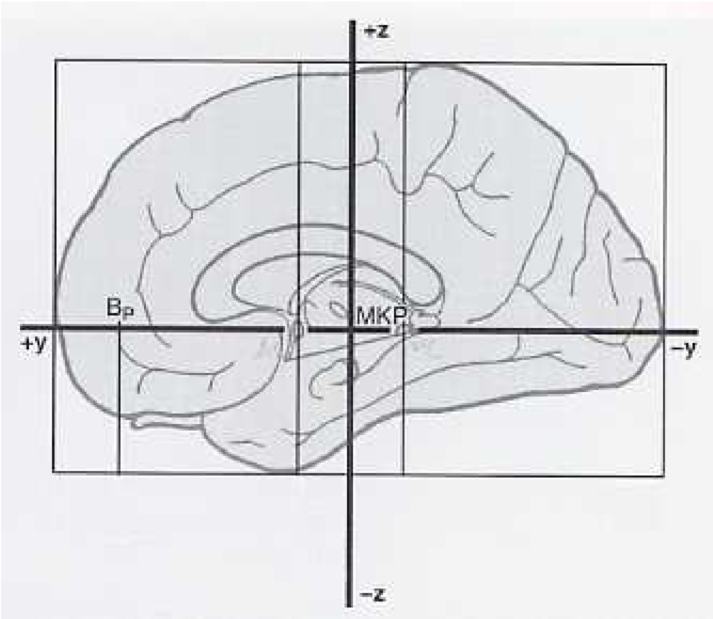

1 Harmonic

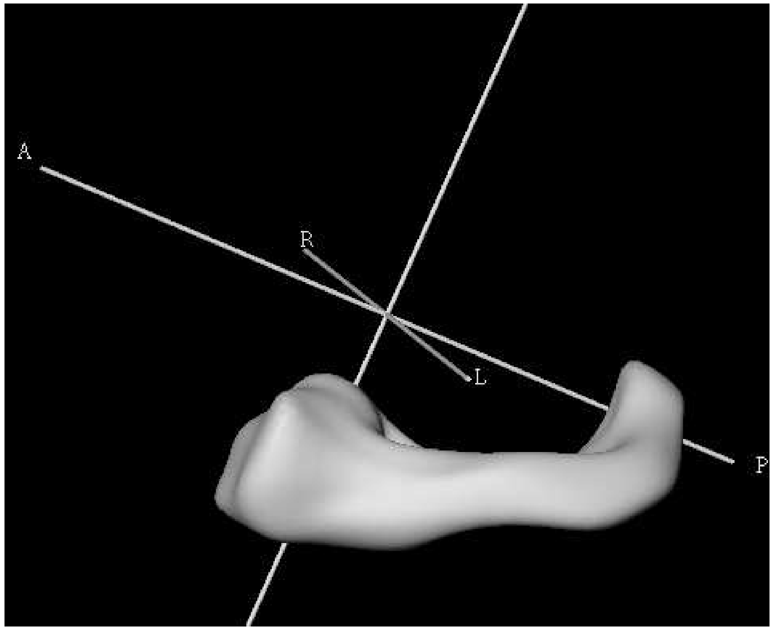

3 Harmonics


6 Harmonics

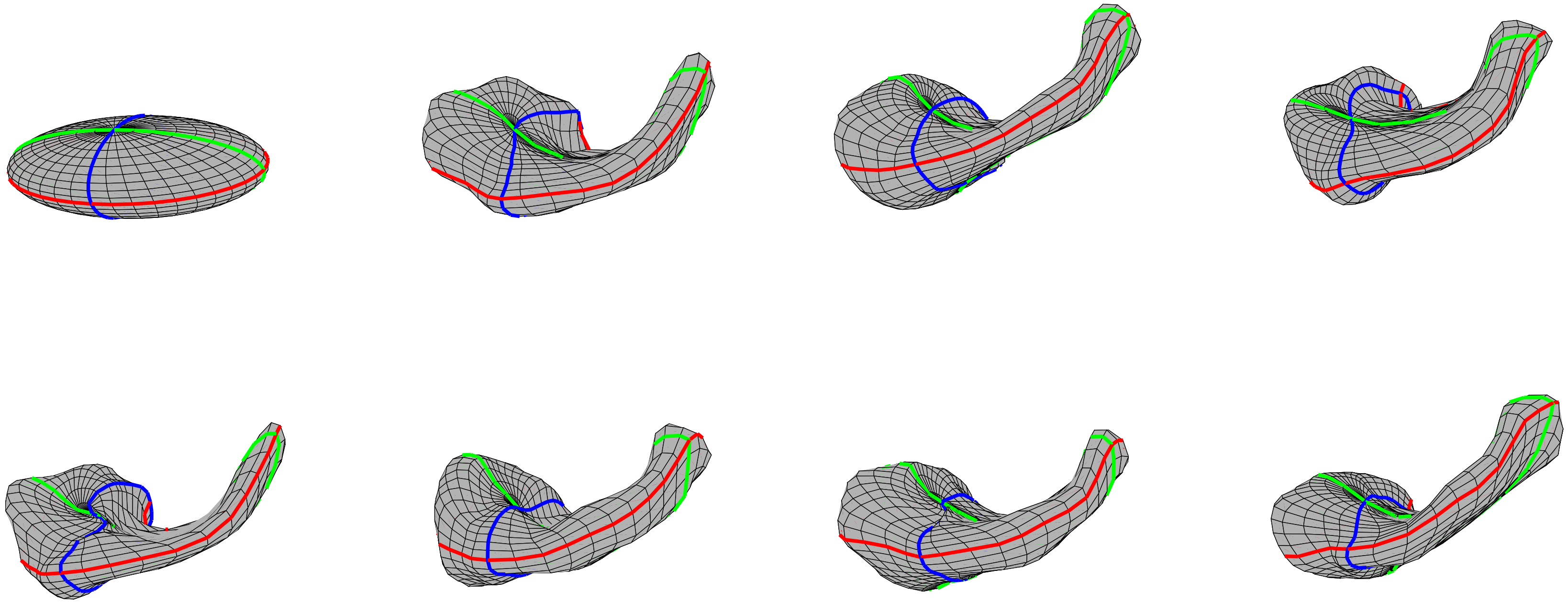

10 Harmonics

Normalization in Object Space: Midsagittal Plane and AC-PC Line





Normalization in Parameter Space



Computing the Statistical Model

$$\text{mean model:} \quad \bar{\mathbf{c}} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{c}_i$$

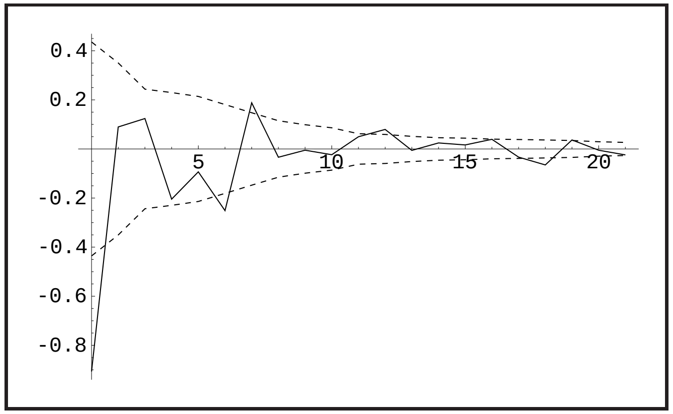
$$\text{shape deviation:} \quad d\mathbf{c}_i = (\mathbf{c}_i - \bar{\mathbf{c}})$$

$$\Sigma = \frac{1}{N-1}\sum_i d\mathbf{c}_i \cdot d\mathbf{c}_i^T$$

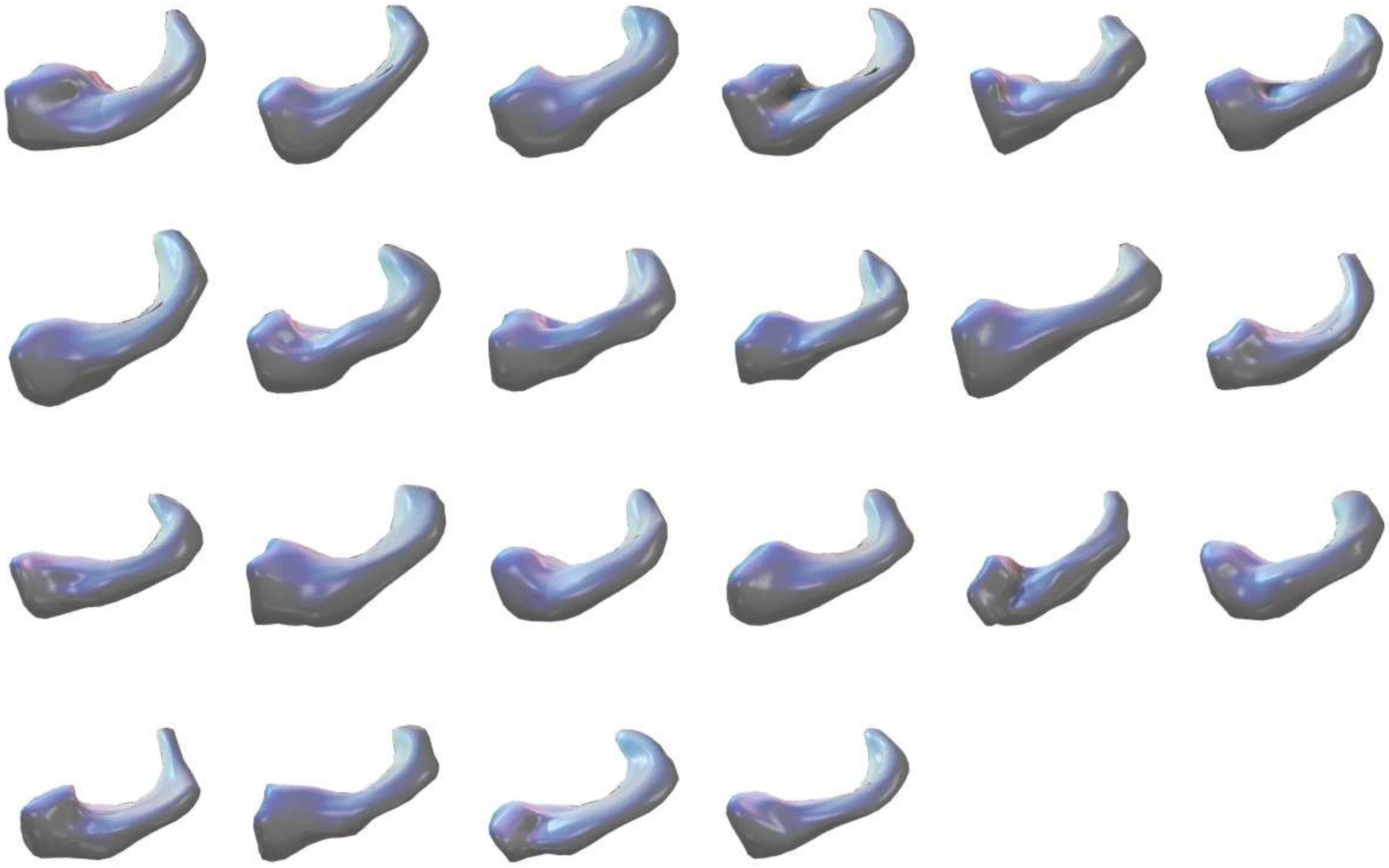
$$\text{eigen analysis:} \quad \Sigma \cdot \mathbf{P} = \mathbf{P} \cdot \Lambda$$

$$\text{individual shape:} \quad \mathbf{c}_i = \bar{\mathbf{c}} + \mathbf{P} \cdot \mathbf{b}_i$$

$$\text{weights:} \quad \mathbf{b}_i = \mathbf{P}^T(\mathbf{c}_i - \bar{\mathbf{c}})$$



Individual Left-Hippocampi

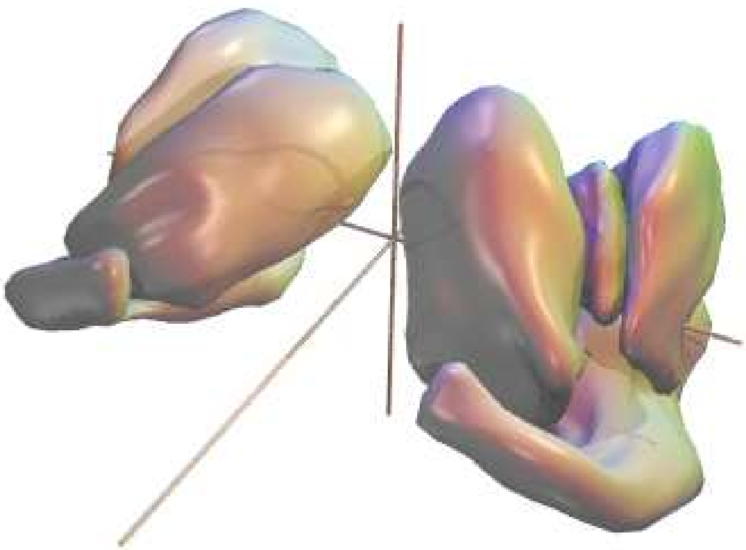


Eigendeformations of Left-Hippocampus

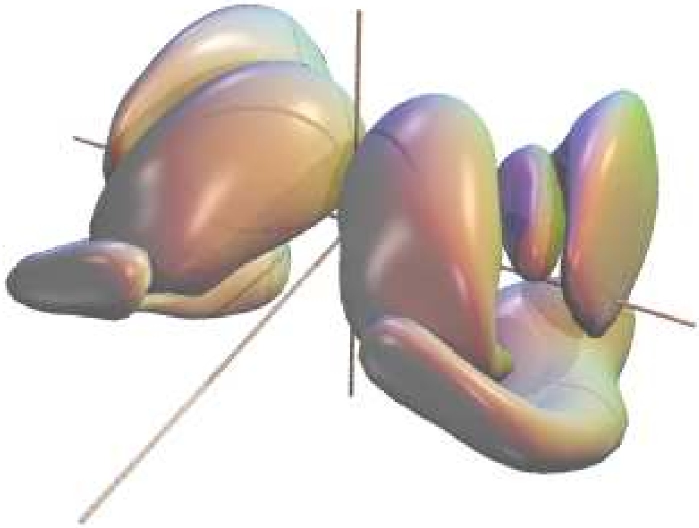
$b_1 = -2\sqrt{\lambda_1}$ $b_1 = -1\sqrt{\lambda_1}$ $b_1 = 0$ $b_1 = 1\sqrt{\lambda_1}$ $b_1 = 2\sqrt{\lambda_1}$

$b_2 = -2\sqrt{\lambda_2}$ $b_2 = -1\sqrt{\lambda_2}$ $b_2 = 0$ $b_2 = 1\sqrt{\lambda_2}$ $b_2 = 2\sqrt{\lambda_2}$

Individual and Average Brain Objects

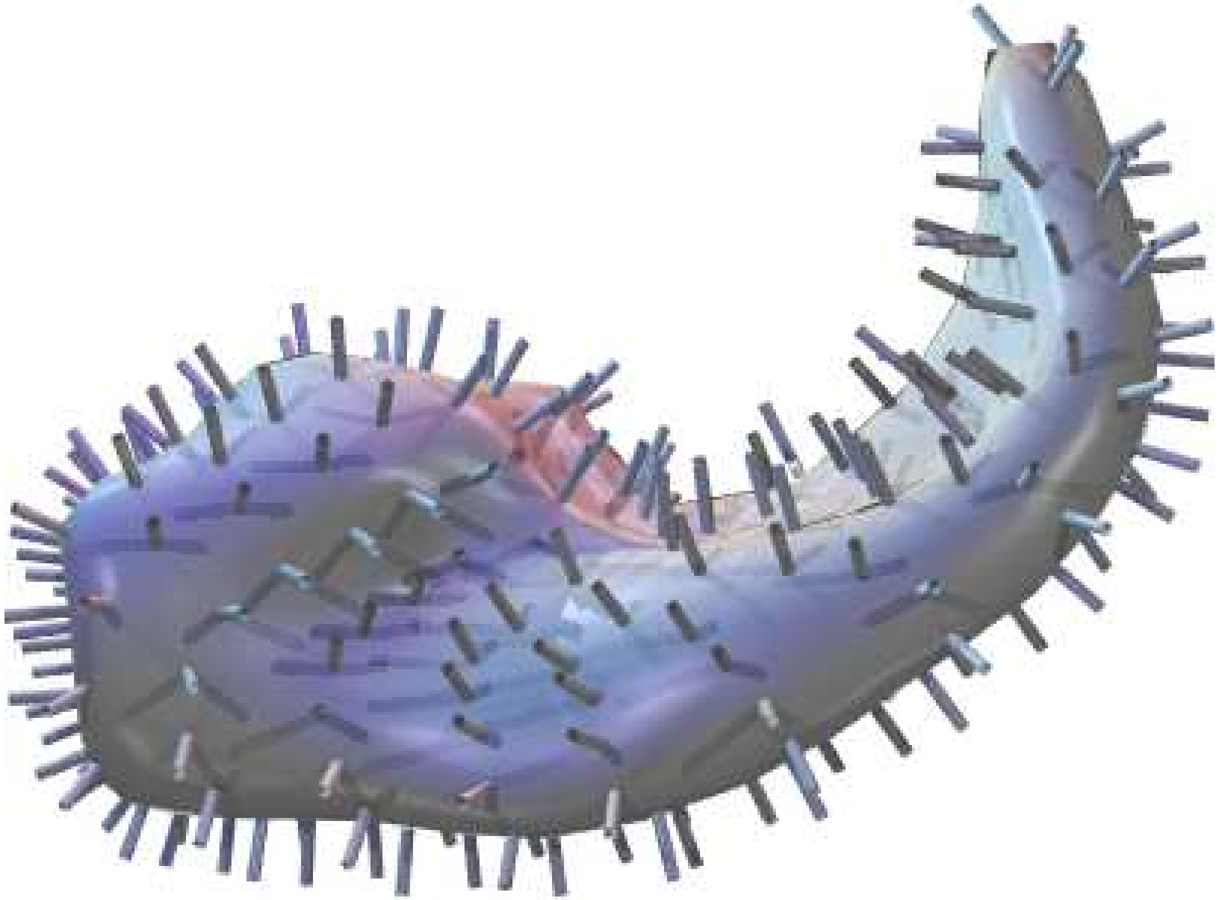


Individual Structures

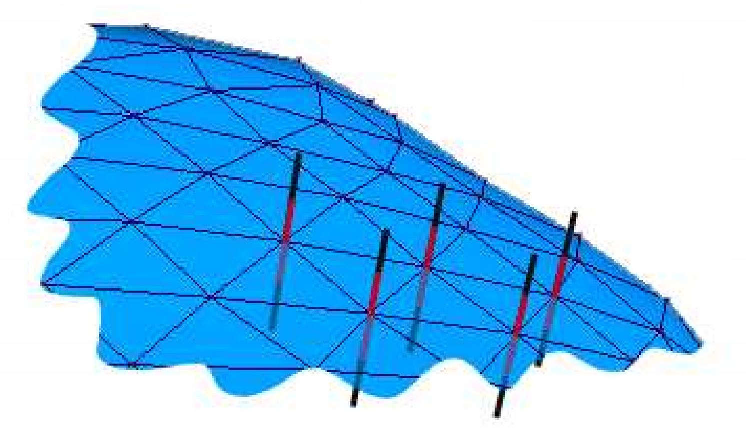


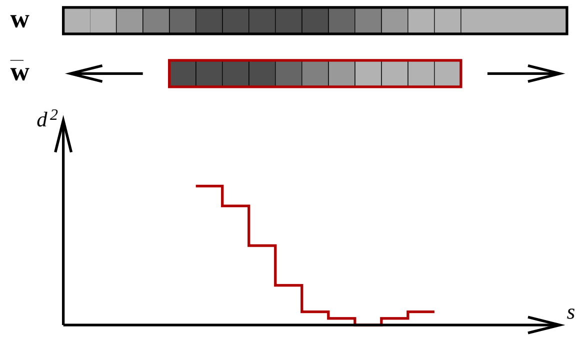
Average Models

Modelling Gray Level Appearance



Matching Profiles





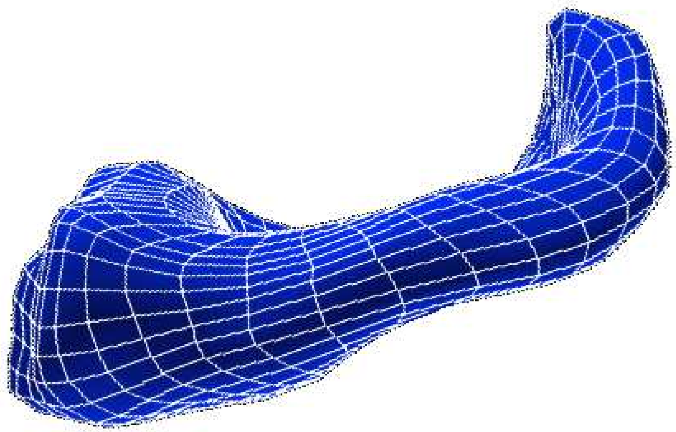
$$d^2_{Maha}(s) = (\mathbf{w}(s) - \overline{\mathbf{w}})\Sigma_{\mathbf{w}}^{-1}(\mathbf{w}(s) - \overline{\mathbf{w}})$$

Object Representations

Surface Points:

Spherical Harmonics:

$$\mathbf{x} = \mathbf{A}\mathbf{c}$$



Local Description
Regular Sampling
Position of Profiles

Global Shape Description
Finding Correspondence
Computing Surface Normals

Computing the Fit

Parameter Space:

- Statistics in spher. harm.: $\mathbf{c} = \overline{\mathbf{c}} + \mathbf{P}_{\mathrm{c}}\mathbf{b}$
- Multiplying by $\mathbf{A}$: $\mathbf{A}\mathbf{c} = \mathbf{A}\overline{\mathbf{c}} + \mathbf{A}\mathbf{P}_{\mathrm{c}}\mathbf{b}$

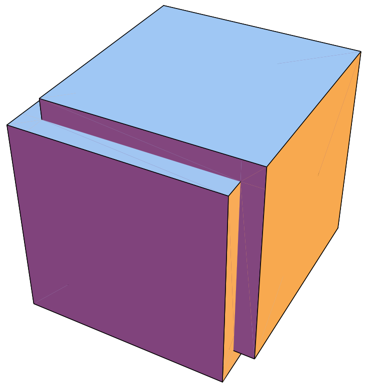
Object Space:

- Statistics in coordinates: $\mathbf{x} = \overline{\mathbf{x}} + \mathbf{P}_{\mathrm{x}}\mathbf{b}$
- Altering coordinates with $d\mathbf{x}$: $(\mathbf{x} + d\mathbf{x}) = \overline{\mathbf{x}} + \mathbf{P}_{\mathrm{x}}(\mathbf{b} + d\mathbf{b})$
- Set of eq. to solve: $d\mathbf{x} = \mathbf{P}_{\mathrm{x}} d\mathbf{b}$

Validation: Volume Overlap

Test Object

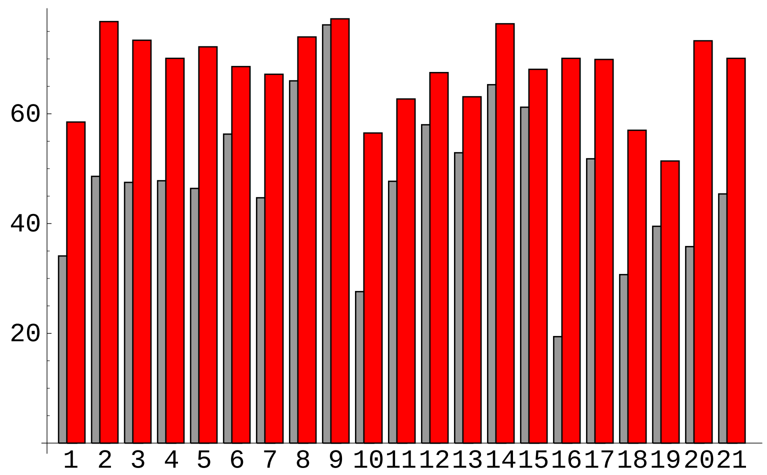
Two cubes of 10x10x10 voxels, one shifted along its space diagonal by 1 voxel:



Overlap measure $= \frac{A \cap B}{A \cup B} = 57\%$

Hippocampus

Overlap measure between manual and automatic segmentation before (gray) and after (red) deformation:



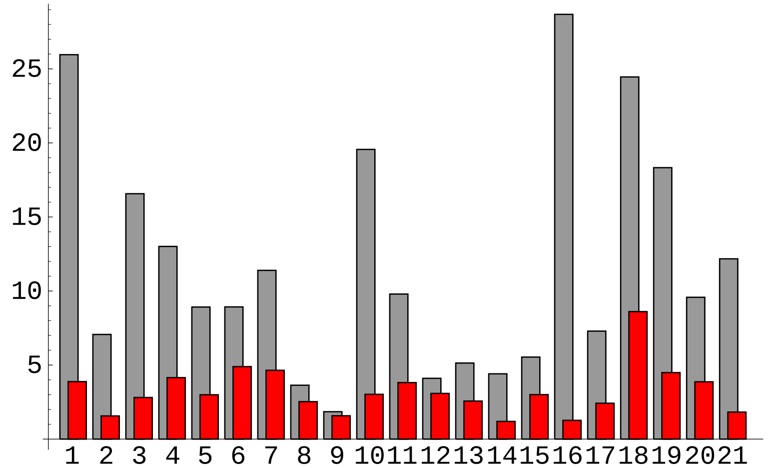
Validation: Surface Distance

Parseval's theorem:

$$\oint \| \mathbf{x}(\mathbf{u}) \|^2 \, d\mathbf{u} = \sum_{l=0}^{\infty} \sum_{m=-l}^{l} | \mathbf{c} |^2 = 4\pi \cdot \mathrm{MSD}$$

MSD stands for "mean squared distance" measured from the origin of the coordinate system.

Average squared distances in mm^2 between manual and automatic segmentation before (gray) and after (red) deformation:



Conclusions and Open Issues

- Conclusions
  - Fully automatic 3-D segmentation
  - Model includes geometry and gray-level profiles
  - Statistical shape models for several brain structures
  - Reproducible results
  - Good approximation to point-to-point correspondence
  - Comprehensive tests and validation
- Open issues
  - Point-to-point correspondence in 3-D
  - Robustness of statistics
  - Limited to simply-connected objects
  - Segmentation of diseased organs