Three-dimensional Model-based Segmentation

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- State-of-the-art
- Status of own research
  - ETH approach
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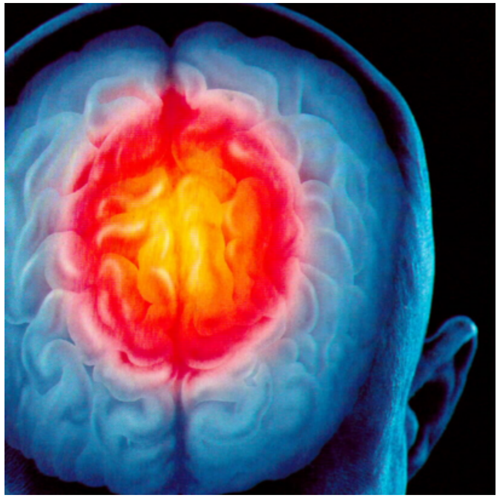
Motivation, Driving Problems

- large increase of amount of medical image data sets
- 3-D and 4-D images become information source in various research domains
- volume images carry detailed morphological and functional information
- need for computer-assisted tools for
  - extraction/representation of anatomical structures
  - morphometric measurements and shape analysis
- Problem: lack of appropriate analysis tools (efficiency, reliability)

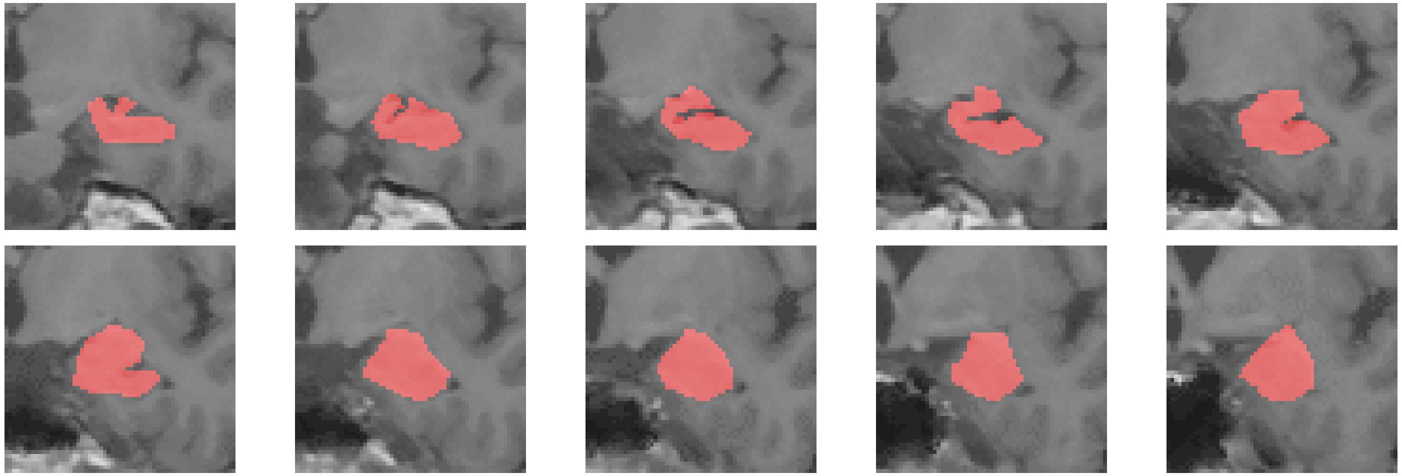
Non-invasive imaging: in-vivo studies, morphometry, function, temporal studies



Imaging technologies are changing the way science is done

(Science, Vol. 261, July 1993, R.P. Crease)

Manual 3-D Segmentation



Advantages: Interactive

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

Methods for morphometric analysis of brain structures

- Atlas-based subdivision of brain images:
  Mazziota, 1995 ICBM / Warfield, 1996
  Christensen, Vannier, Miller 1997
  Ayache and Thirion 1996 / Evans and Collignon 1995
- Model-based segmentation of brain structures:
  Cootes and Taylor, 1995, 1998 / Chakraborty, 1996
  Delinguette, 1997 / Duncan and Staib, 1996
  Vemuri, 1996 / Kelemen, Szekely, Gerig, 1996

Automatic Segmentation: Related Work

- L.H. Staib & J.S. Duncan: 3D fourier organ models, region and gradient based segmentation.

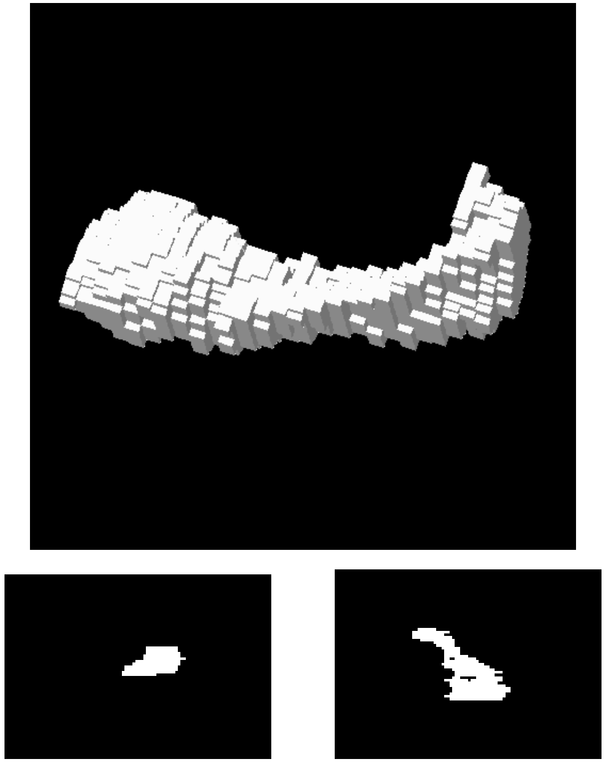
- T.F. Cootes & C.J. Taylor: 2D statistical organ models, modelling gray level appearance, least-squares based segmentation.

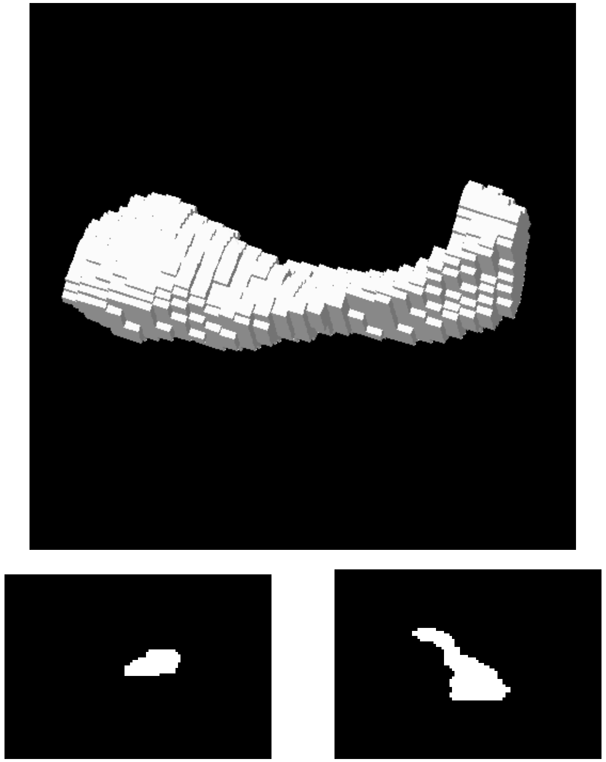
- G. Szekely et al.: 2D statistical organ models, gradient based segmentation

- 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:

$$\mathbf{r}(\theta,\phi) = \begin{pmatrix} x(\theta,\phi) \\ y(\theta,\phi) \\ z(\theta,\phi) \end{pmatrix}$$

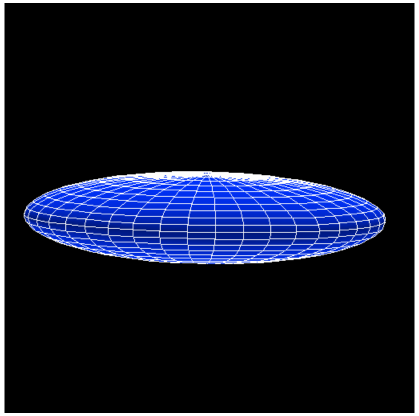
series of orthogonal basis functions:

$$\mathbf{r}(\theta,\phi) = \sum_{k=0}^{K} \sum_{m=-k}^{k} \mathbf{c}_k^m Y_k^m(\theta,\phi)$$

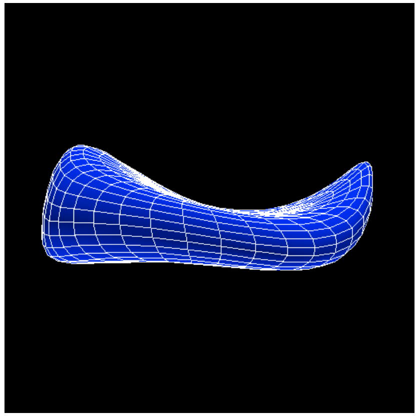
descriptors:

$$\mathbf{c}_k^m = \begin{pmatrix} c_{x_k}^{\,m} \\ c_{y_k}^{\,m} \\ c_{z_k}^{\,m} \end{pmatrix}$$

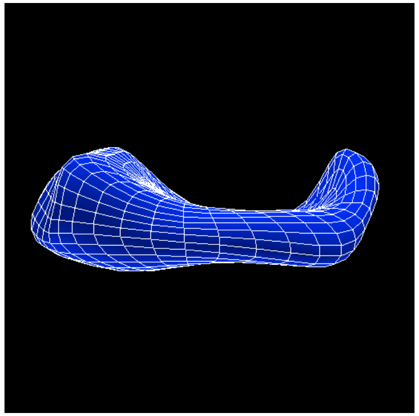
Parametrization 2



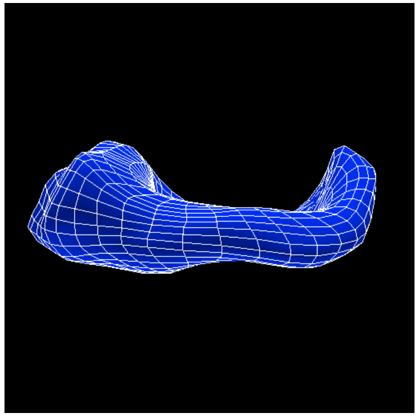
1 Harmonic



3 Harmonics



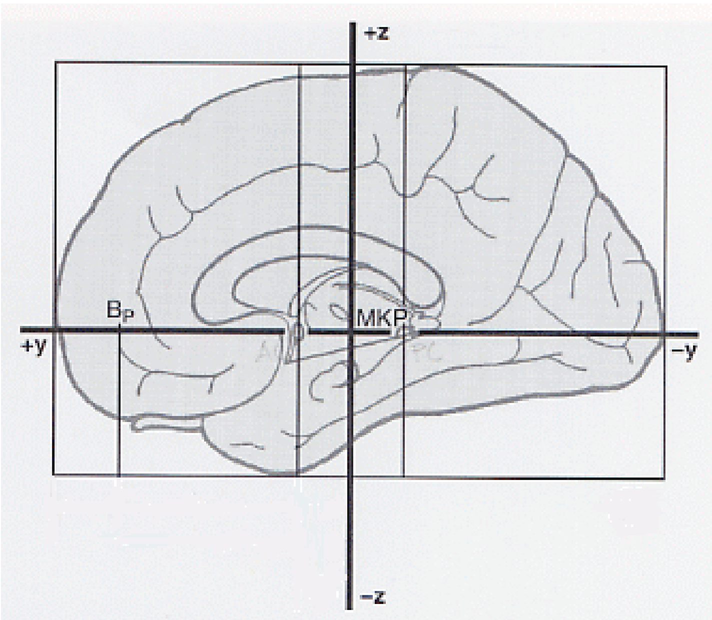
6 Harmonics

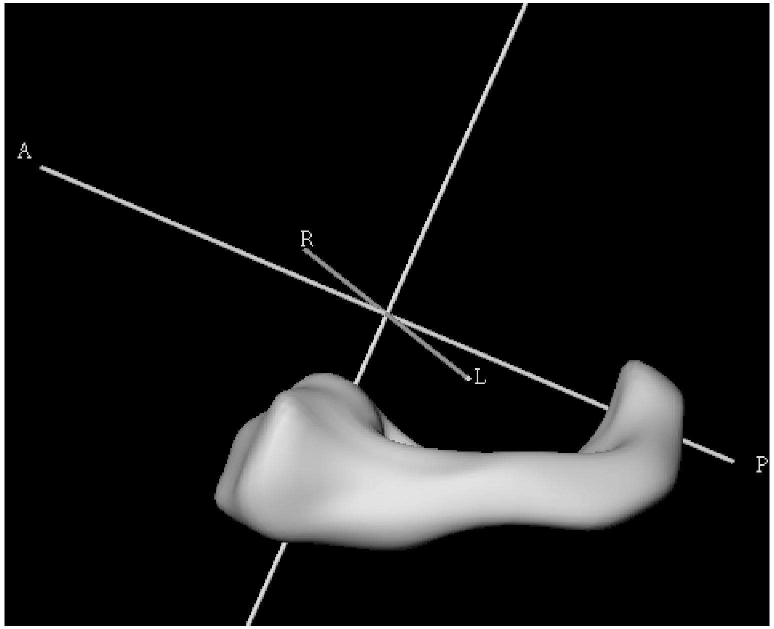


10 Harmonics

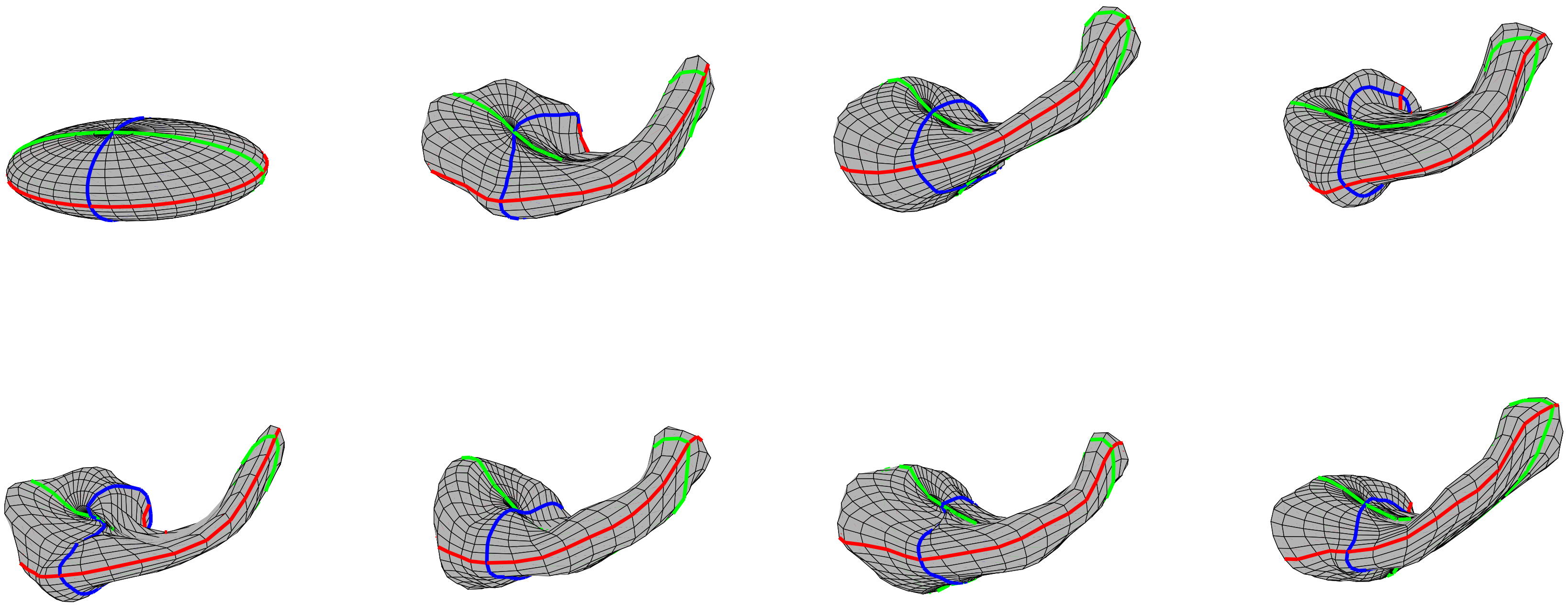
Normalization in Object Space

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



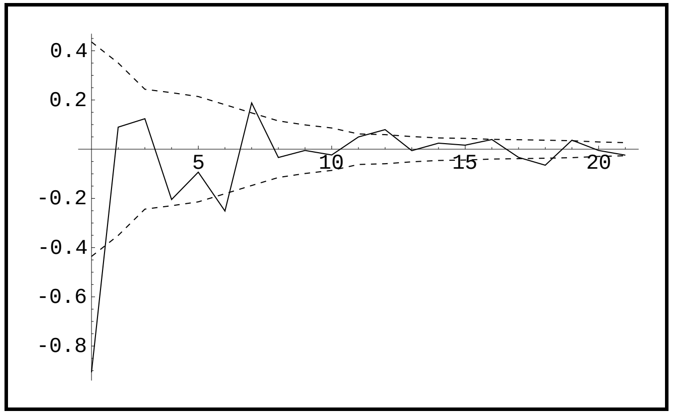


Normalization in Parameter Space

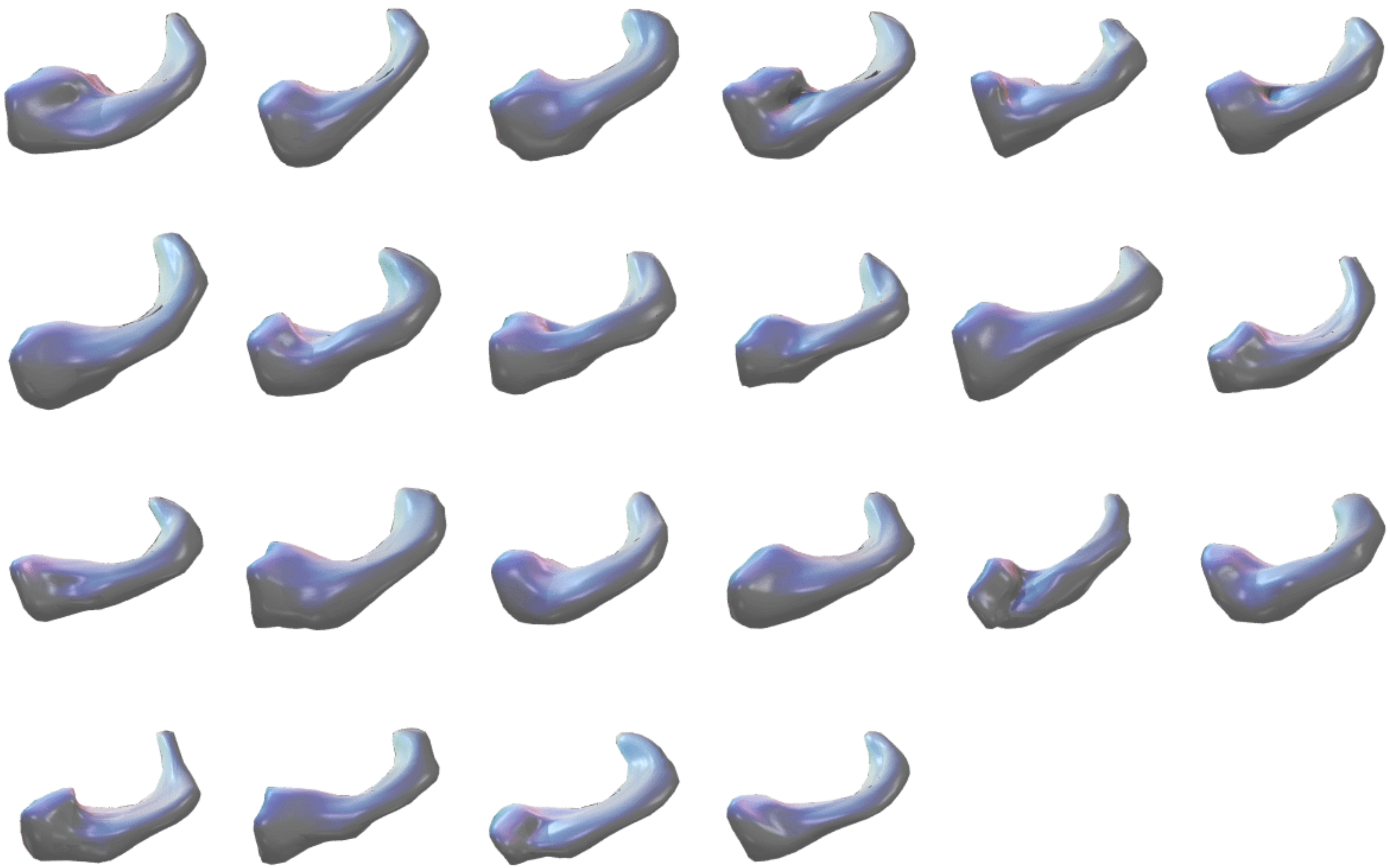


Computing the Statistical Model

$$
\begin{aligned}
\text{mean model:} \quad \bar{\mathbf{c}} &= \frac{1}{N}\sum_{i=1}^{N}\mathbf{c}_i \\
\text{shape deviation:} \quad d\mathbf{c}_i &= (\mathbf{c}_i - \bar{\mathbf{c}}) \\
\Sigma &= \frac{1}{N-1}\sum_{i} d\mathbf{c}_i \cdot d\mathbf{c}_i^T \\
\text{eigen analysis:} \quad \Sigma \cdot \mathbf{P} &= \mathbf{P} \cdot \Lambda \\
\text{individual shape:} \quad \mathbf{c}_i &= \bar{\mathbf{c}} + \mathbf{P} \cdot \mathbf{b}_i \\
\text{weights:} \quad \mathbf{b}_i &= \mathbf{P}^T(\mathbf{c}_i - \bar{\mathbf{c}})
\end{aligned}
$$



Individual Left-Hippocampi

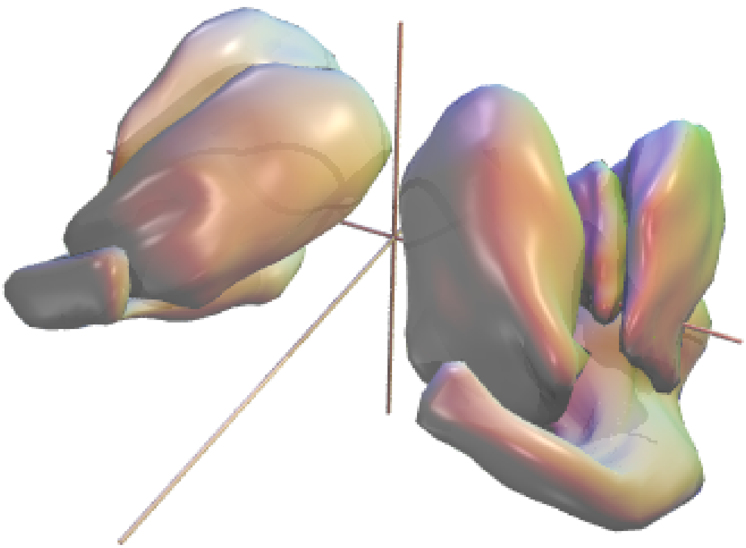


Eigendeformations of Left-Hippocampus

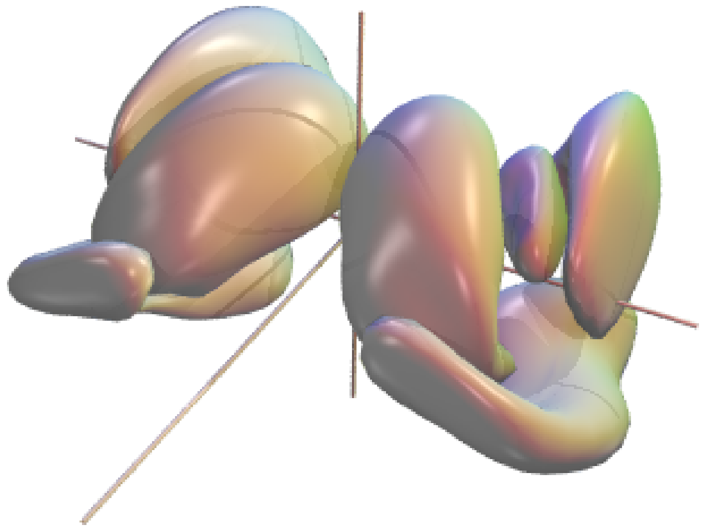
$b_1 = -2\sqrt{\lambda_1}$ $b_1 = -1\sqrt{\lambda_1}$ $b_1 = 0$ $b_1 = 1\sqrt{\lambda_1}$ $b_1 = 2\sqrt{\lambda_1}$

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

Individual and Average Brain Objects

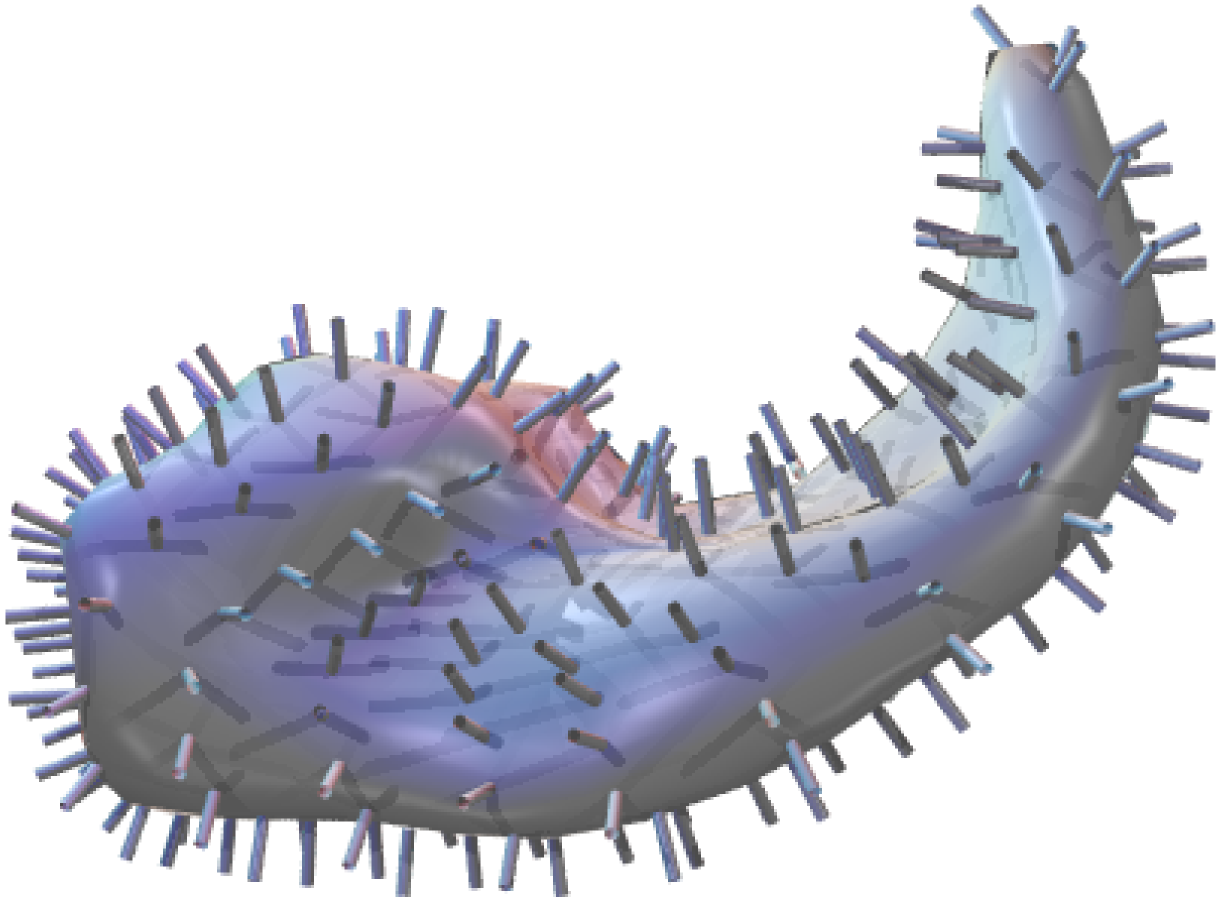


Individual Structures

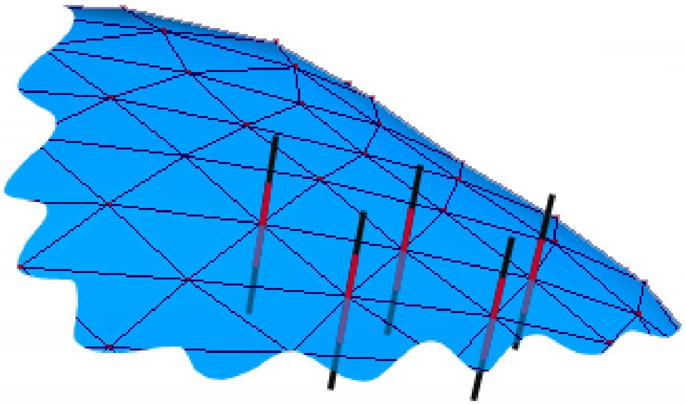


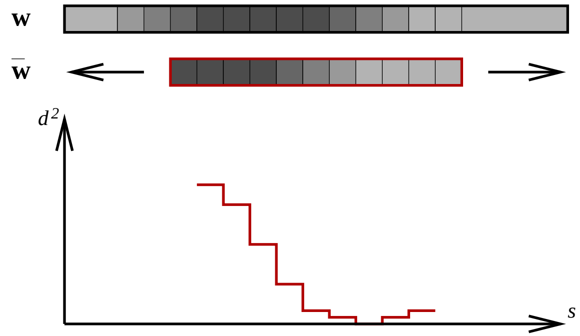
Average Models

Modelling Gray Level Appearance



Matching Profiles





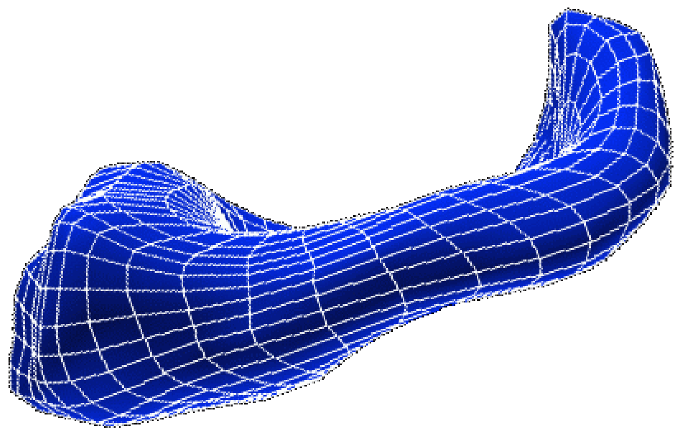
$$d^2_{Maha}(s) = (\mathbf{w}(s) - \overline{\mathbf{w}})\Sigma_{\mathbf{w}}^{-1}(\mathbf{w}(s) - \overline{\mathbf{w}})$$

Object Representations

Surface Points:

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

Spherical Harmonics:



Local Description
Regular Sampling
Position of Profiles

Global Shape Description
Finding Correspondence
Computing Surface Normals

Computing the Fit

Parameter Space:

Statistics in spher. harm.: $$\mathbf{c} = \bar{\mathbf{c}} + \mathbf{P_c b}$$

Multiplying by $\mathbf{A}$: $$\mathbf{Ac} = \mathbf{A}\bar{\mathbf{c}} + \mathbf{AP_c b}$$

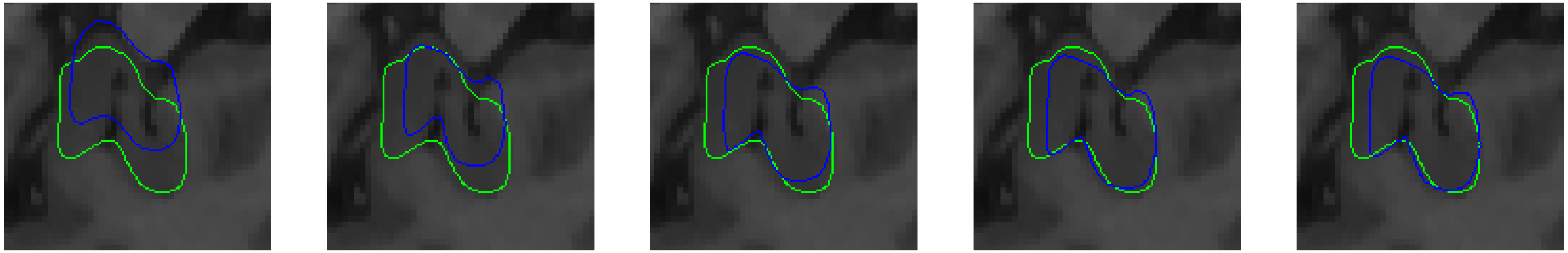
Object Space:

Statistics in coordinates: $$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P_x b}$$

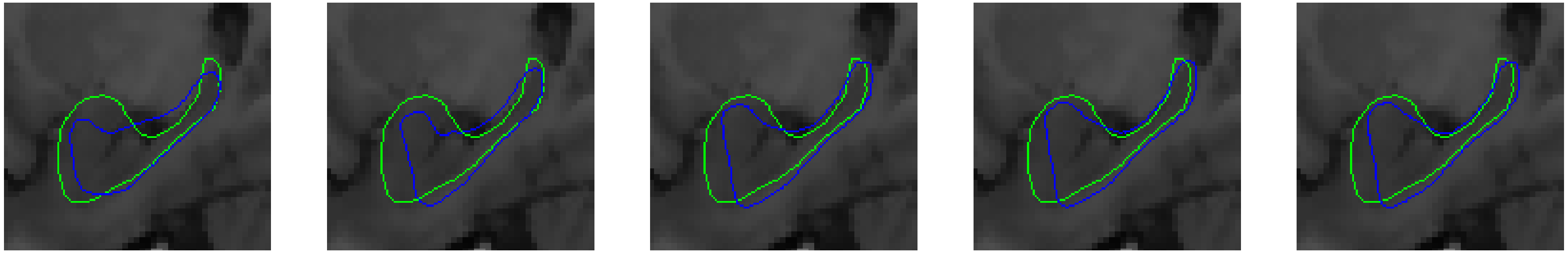
Altering coordinates with $d\mathbf{x}$: $$(\mathbf{x} + d\mathbf{x}) = \bar{\mathbf{x}} + \mathbf{P_x}(\mathbf{b} + d\mathbf{b})$$

Set of eq. to solve: $$d\mathbf{x} = \mathbf{P_x}d\mathbf{b}$$

Segmentation Results 1

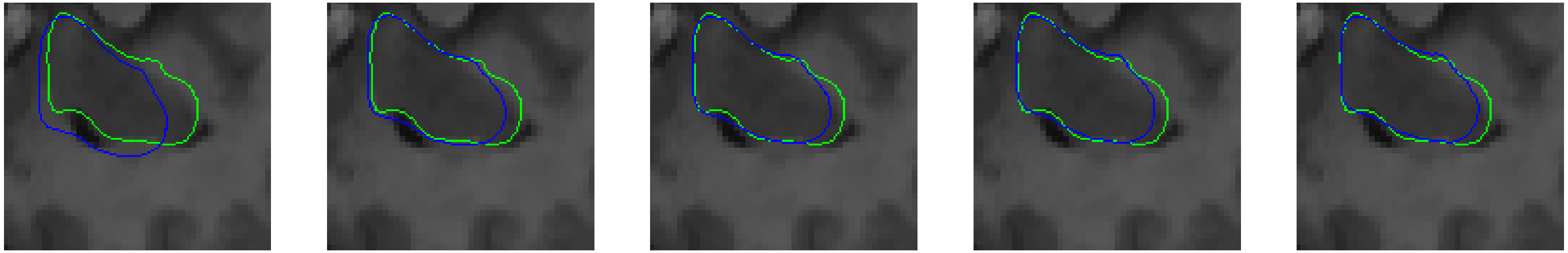


Axial

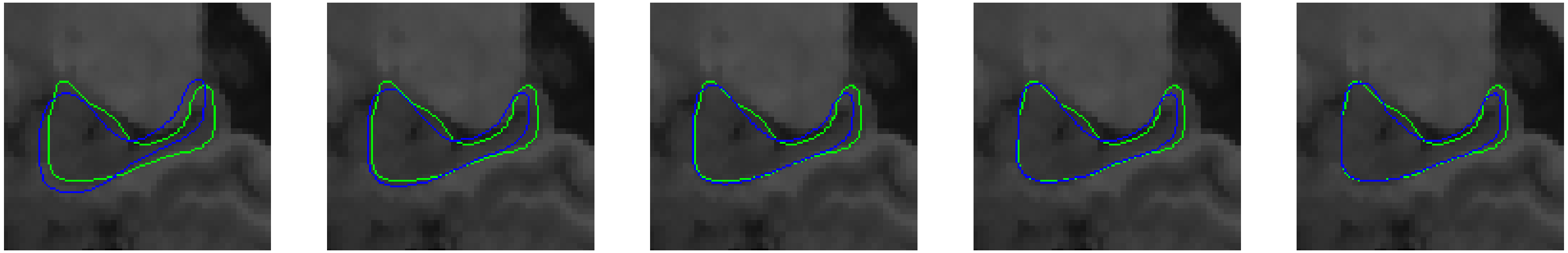


Saggital

Segmentation Results 2



Axial

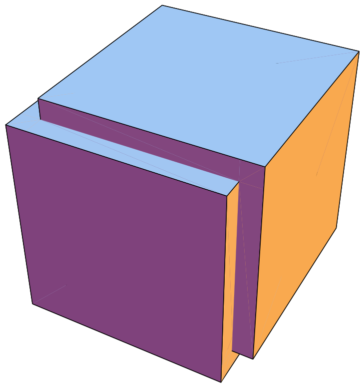


Saggital

Validation: Volume Overlap

Test Object

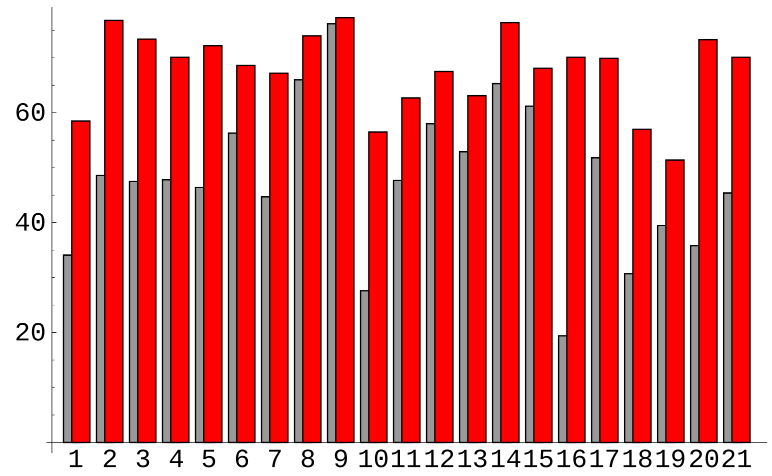
Two cubes of 10x10x10 voxels, one shifted along its space diagonal by 1 voxel:



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

Hippocampus

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



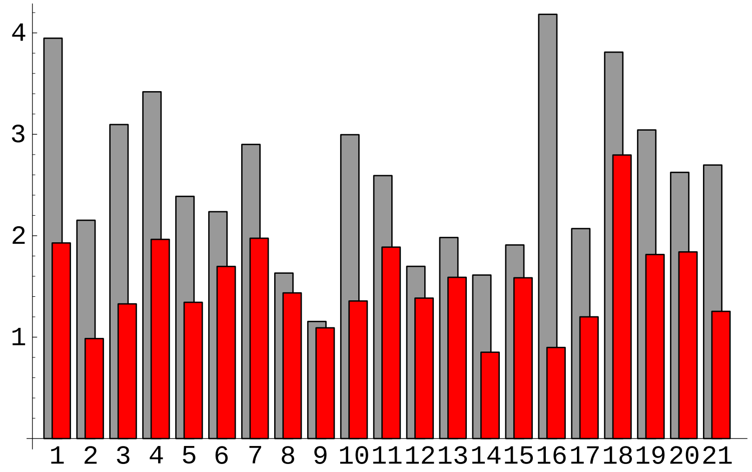
Validation: Surface Distance

Parseval's theorem:

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

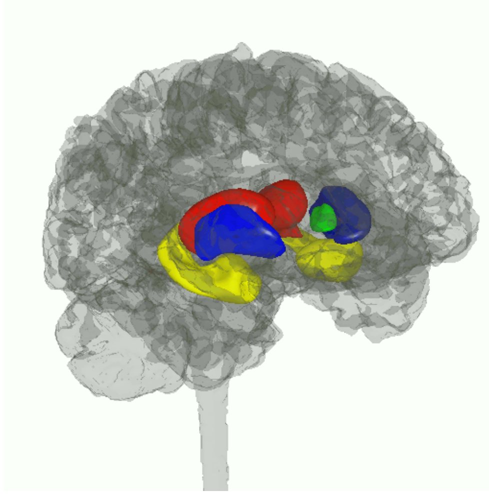
MSD stands for "mean squared distance" measured from the origin of the coordinate system.

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



Conclusions

- Fully automatic 3-D segmentation
- Model includes geometry and gray-level profiles
- Statistical shape models for several brain structures
- Reproducible results
- Computation time: 2-5’ on SUN Ultra-10
- Good approximation to point-to-point correspondence
- Comprehensive tests and validation



Open Issues

Statistical Surface Model:

- Global shape model, no access to local shape properties
- No representation of figure vs. subfigures
- Simultaneous segmentation of set of anatomical shapes
- Robustness of statistics (PCA with small sample number and high dimensionality)
- Number of training shapes?
- Constrained segmentation: too restrictive?
- Point-to-point correspondence in 3-D to be improved
- Limited to simply-connected objects
- Segmentation of diseased organs?

Future Directions

- Combination of medial and surface object representation:
  3-D Voronoi skeleton and DSL model
- Generate simulated shape models for testing statistical surface shapes and for the DSL parametrization development
- Test ability of spherical harmonic model and its restricted deformation to cope with local warps as generated by DSL warps
- Apply shape segmentation and representation methods to serial 3-D image data to study progression of disease (make use of correlation)
- Study of shape parameter changes to explain shape changes over time