Introduction Image Analysis & Computer Vision

Guido Gerig

CS/BIOEN 6640 FALL 2010

August 23, 2010

Courses and Seminars related to Research in Image Analysis

NEW in 2010: SoC Image Analysis Track (Director Tom Fletcher) (click)

Fall 2010:

- Image Processing CS 6640/ BIOEN 6640

Spring 2011:

- 3D Computer Vision CS 6320
- Advanced Image Processing CS 6640
- Mathematics of Imaging BIOEN 6500

Fall 2011:

- Image Processing Basics CS 4961
- Image Processing CS 6640

On demand:

- Special Topics Courses: Non-Euclidean Geometry, Non-Param. Stats, ..

Seminars:

- Seminar Imaging "ImageLunch" CS 7938: weekly Mondays 12 to 1.15, WEB 3670

CS/BIOEN 6640 F2010

For class:

- 1) Go to the web-site page: http://www.sci.utah.edu/~gerig/CS6640-F2010/CS6640-F2010.html
- 2) Look over the instructions and syllabus
- 3) Follow the link to "mailing lists" and join the cs6640 mailing lists as in the instructions. Remind them to use a mail address that they actually read (COMING SOON)
- 4) Look at the final and midterm exam dates and mark those on your calendar
- 5) Purchase the book
- 6) Do the first 2 reading assignments.

CS/BIOEN 6640 F2010

For class:

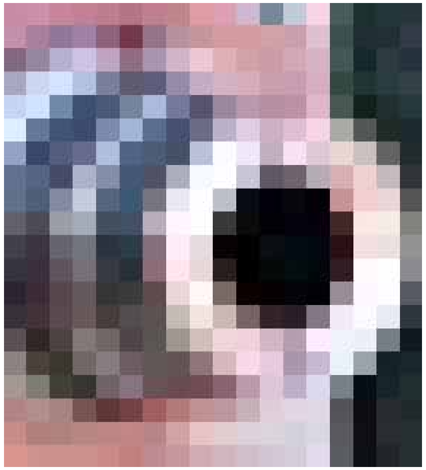
- We will use the uxxxxxxxx email address for communication, please forward the u-email to your personal email if you use another account.
- The web-site provides downloads for additional materials and handouts.
- The syllabus is not completely rigid and fixed, and some topics will develop as the class continues.
- We will primarily use MATLAB (no extensions and additional libraries) for the projects. You can use CADE lab licenses or purchase a personal student license. C++ is an option (see web-page).
- Etc.

Goals

- to tell you what you can do with digital images
- to show you that doing research in computer vision and image analysis is fun and exciting
- to demonstrate that image processing is based on strong mathematical principles, applied to digital images via numerical schemes
- to show you that you can solve typical image processing tasks on your own

Image Sensors

Digital Image

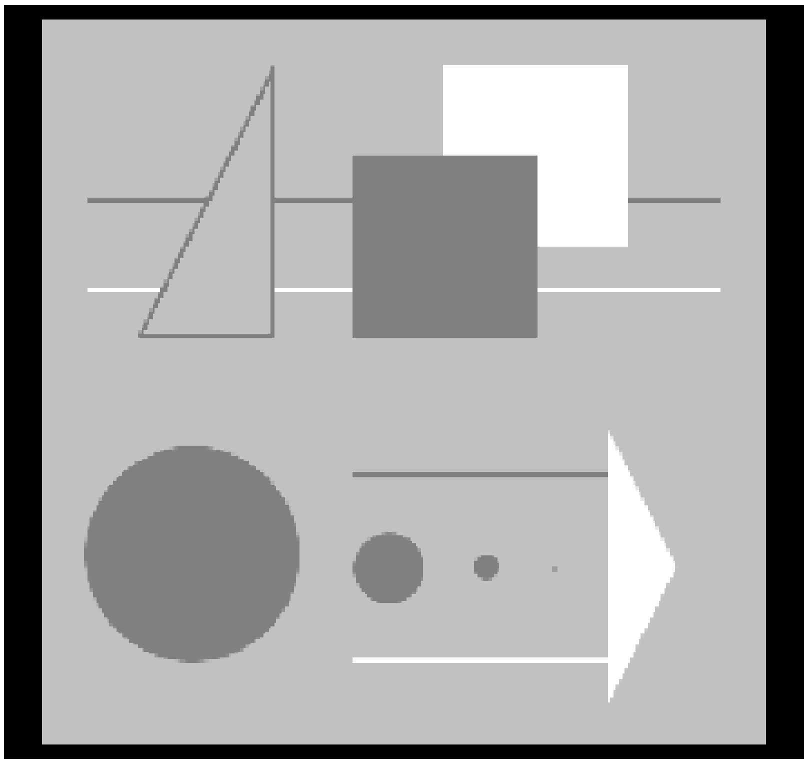


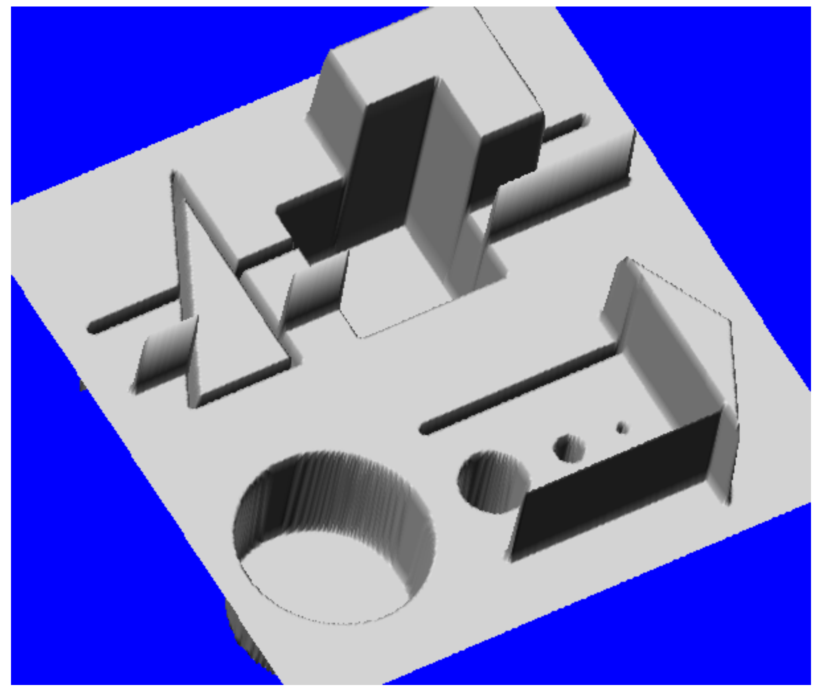
Digital Image

Each cell has number, either a scalar (black and white) or a vector (color).

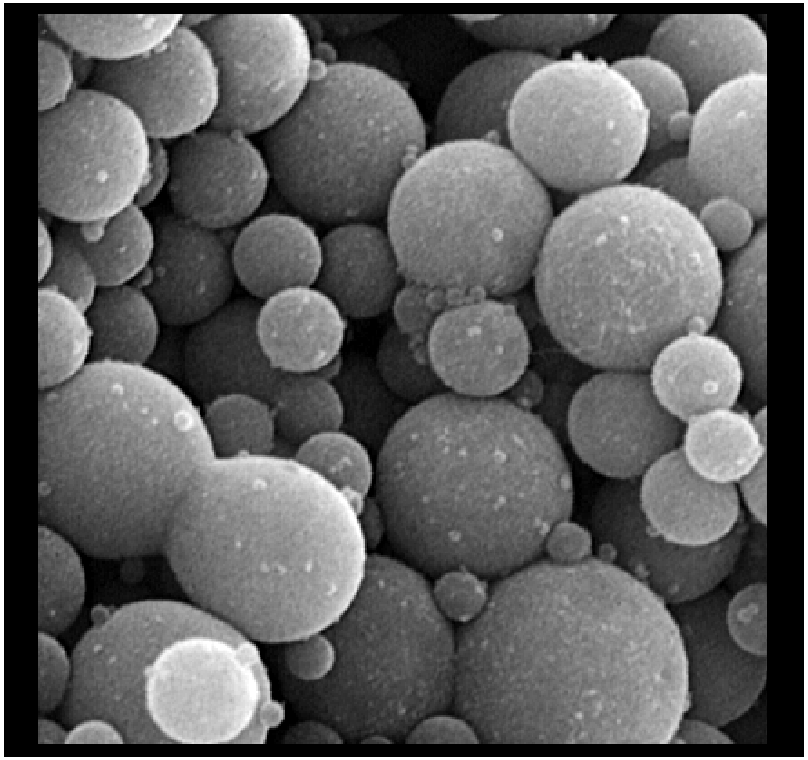
Discrete representation of continuous world (sampling with aperture).

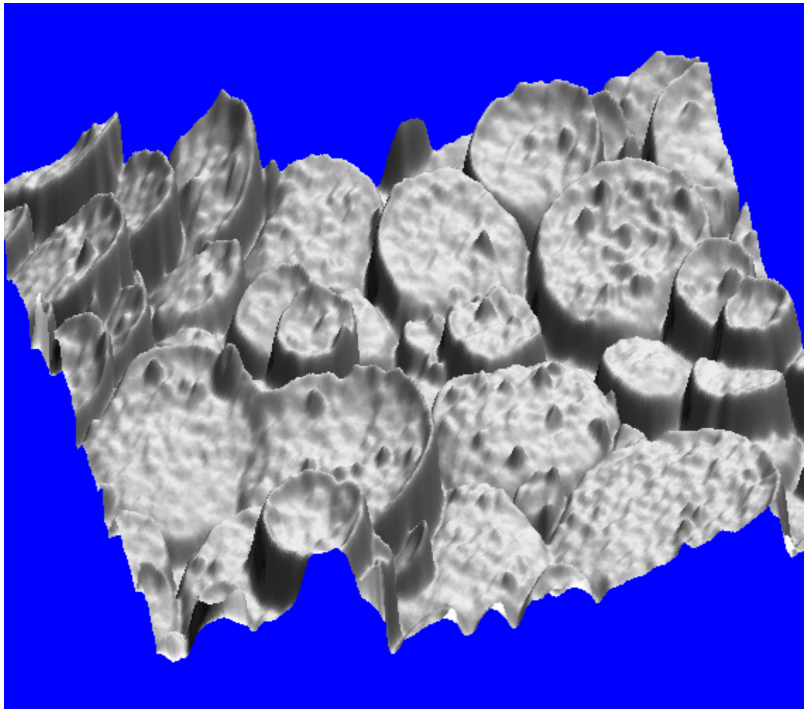
Digital Images





Digital Images





Edges: Sudden change of intensity L

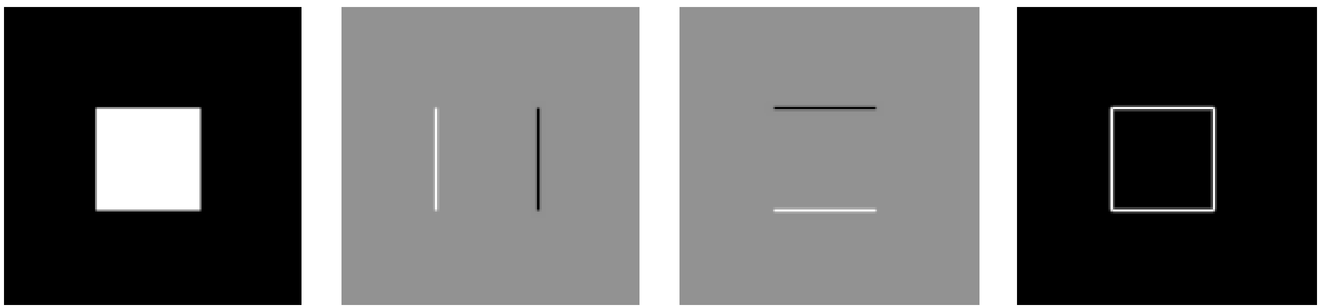
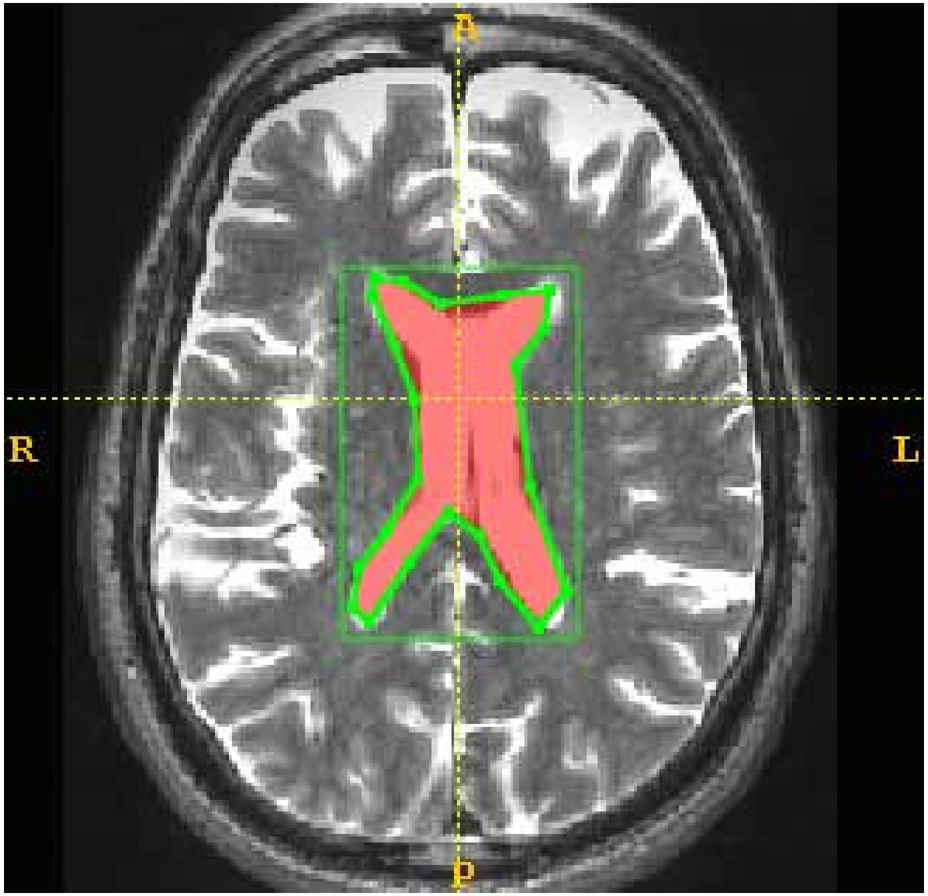


Figure 2.11 The first order derivative of an image gives edges. Left: original test image $L(x, y)$, resolution 256^2. Second: the derivative with respect to x: $\frac{\partial L}{\partial x}$ at scale $\sigma = 1$ pixel. Note the positive and negative edges. Third: the derivative with respect to y: $\frac{\partial L}{\partial y}$ at scale

Segmentation of structures

- User painting/drawing on 2D images ("photoshop")
- Tedious, time consuming, limited precision
- Demonstrate Tool



Deformable Models: SNAKES

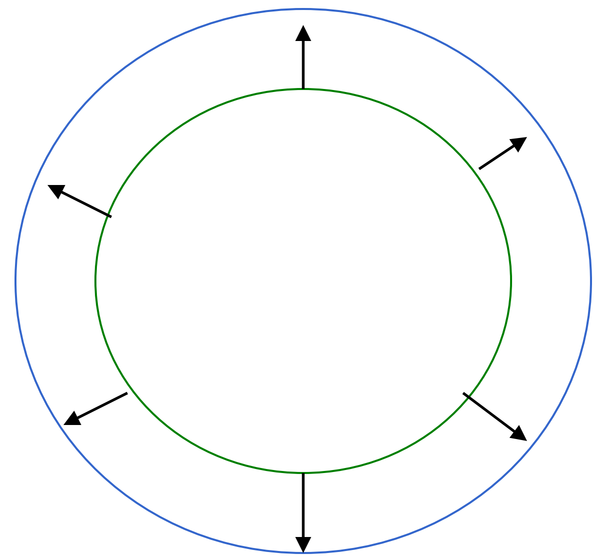
Geodesic Snake formulated as PDE

$$\frac{\partial c(x,t)}{\partial t} = [a]\vec{N}$$

Speed

Curve evolves over time

Normal direction to curve



Deformable Models: SNAKES

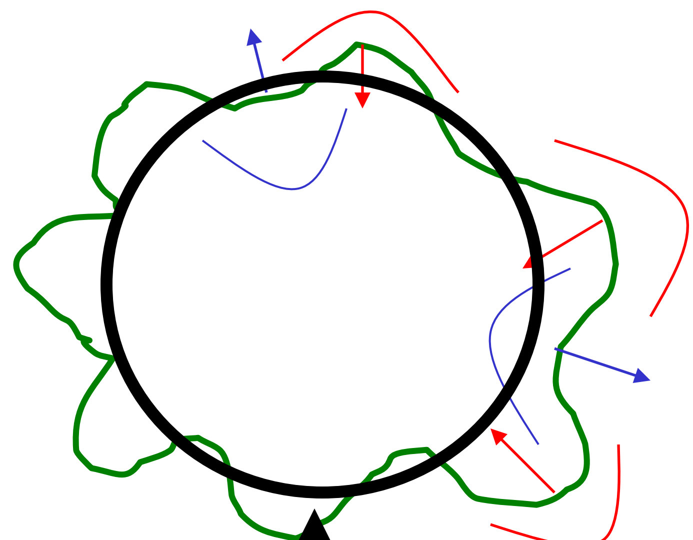
Geodesic Snake:

$$\frac{¶c(x,t)}{¶t} = [k]\overset{®}{N}$$

Curvature (convex, concave)

Curve evolves over time

Normal direction to curve



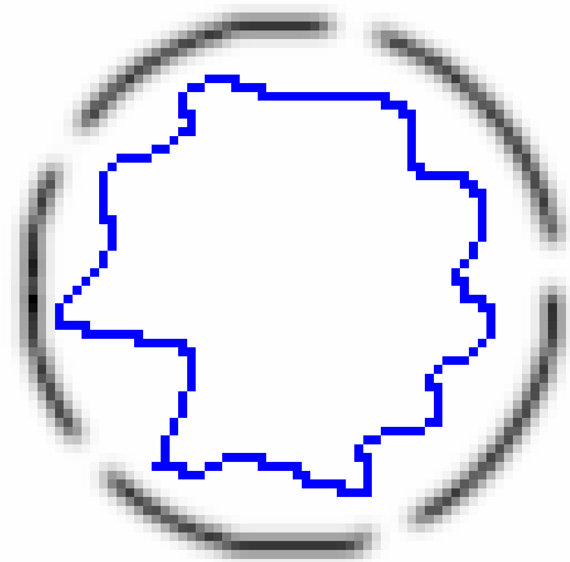
Mathematical solution is circle

Deformable Models: SNAKES

Geodesic Snake:

$$\frac{\P c}{\P t} = [k + a]N$$

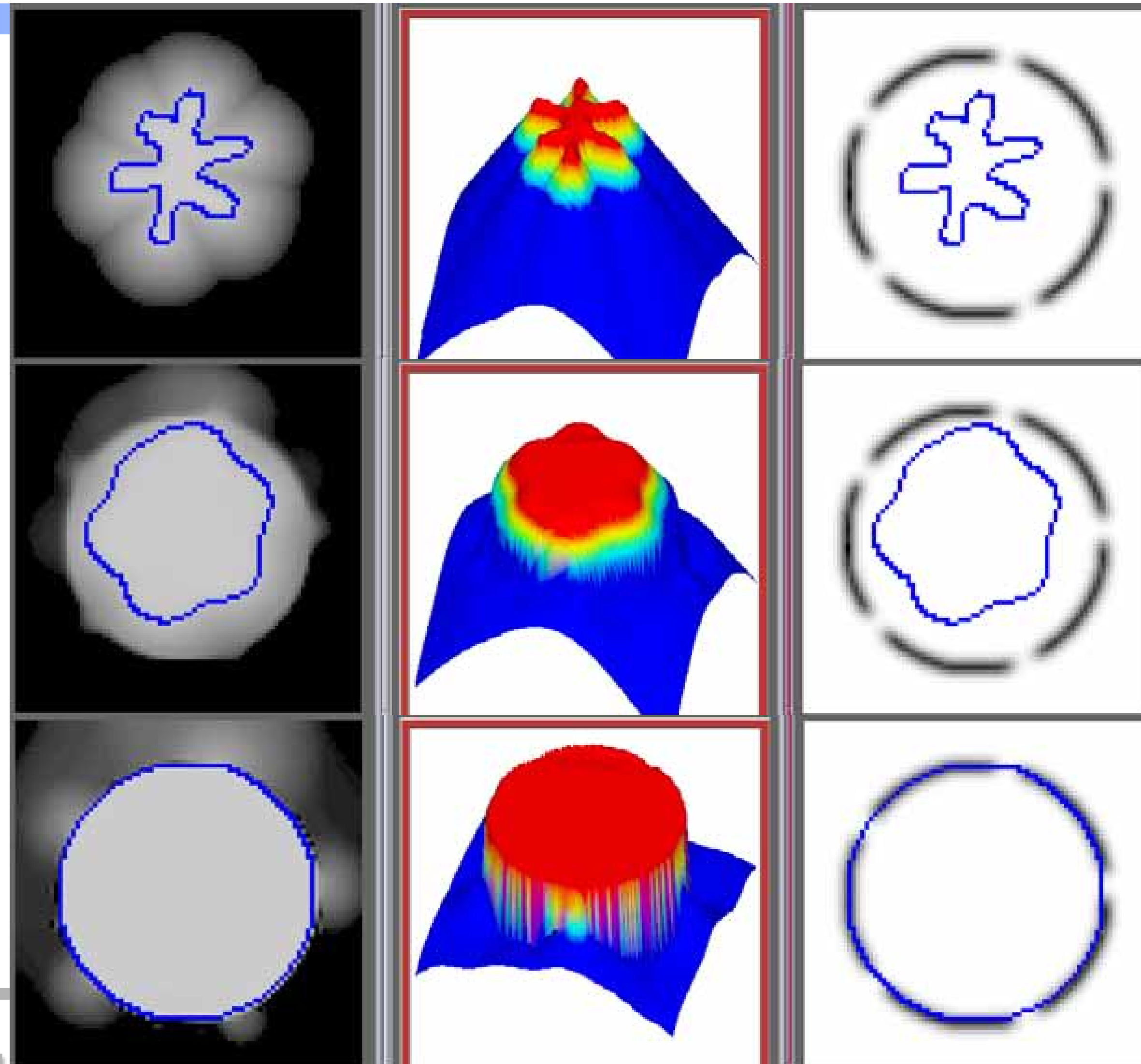
Plus: add a term that stops at boundaries



SCI INSTITUTE

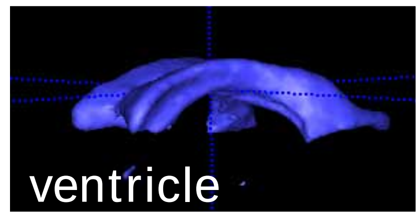
Concept of level-set evolution

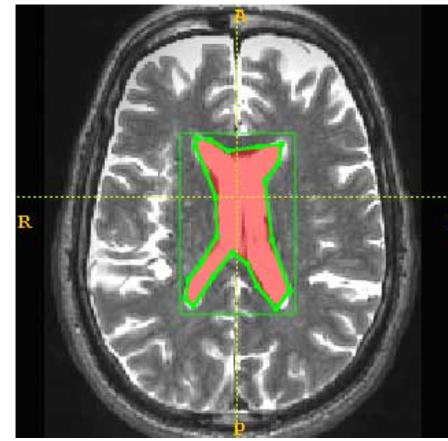
Implementation:
Curve C embedded as zero-level of higher order function j



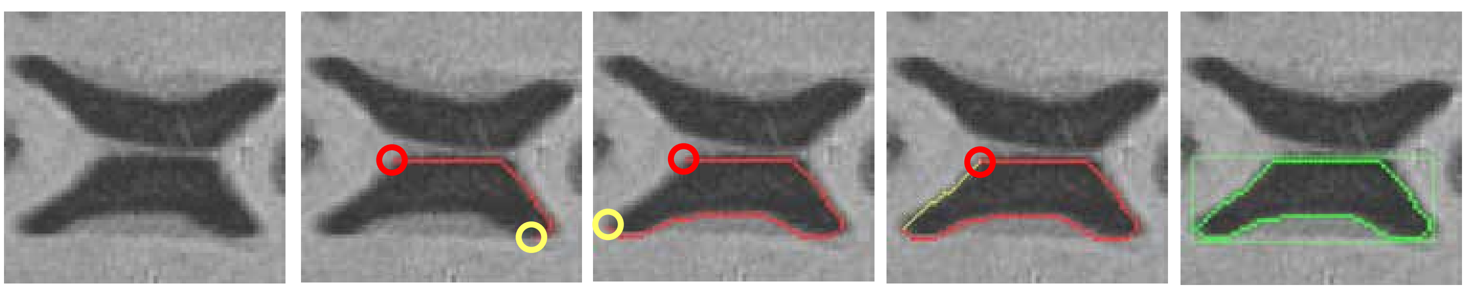
Segmentation tool

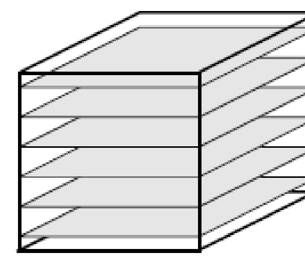
- User painting slice by slice ("photoshop")
- Tedious, time consuming, limited reproducibility
- Painting in 2D intuitive, but what about 3D?



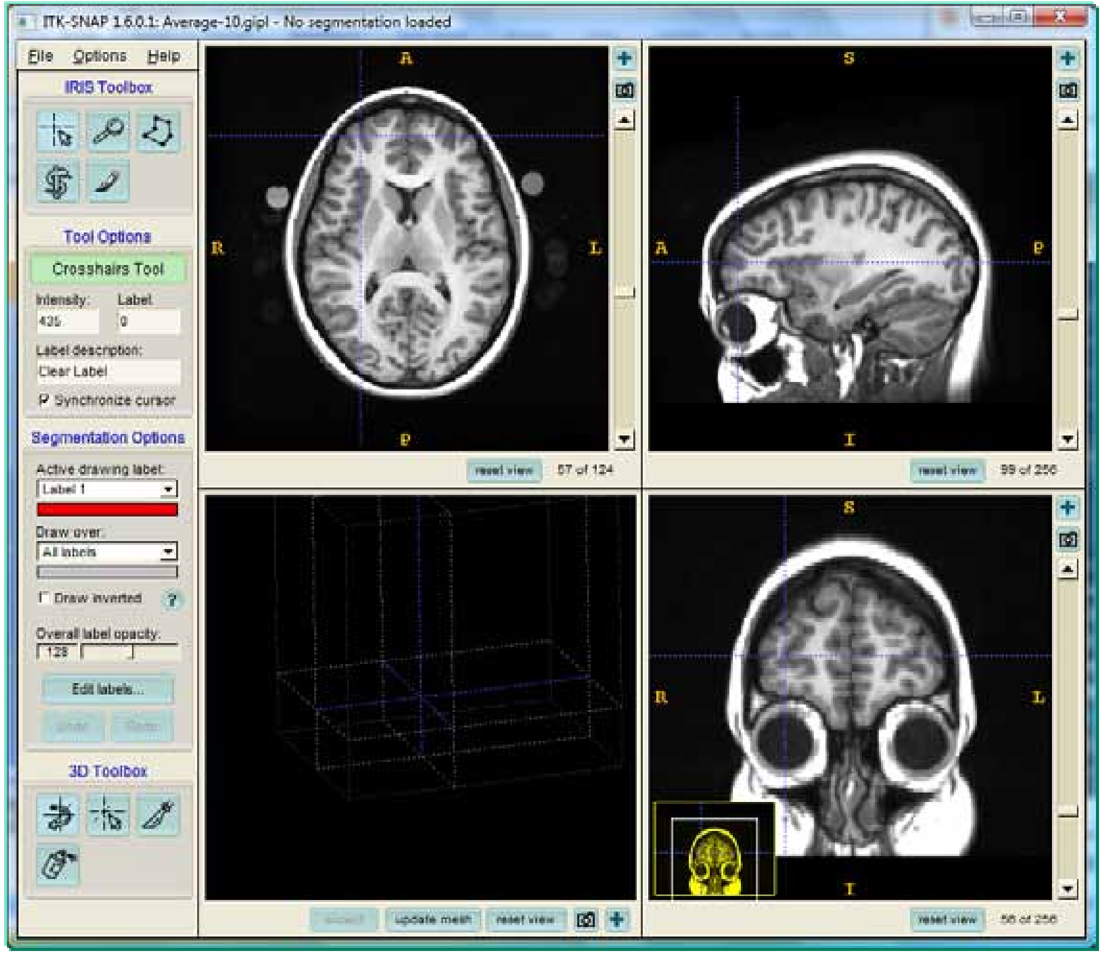


So far: Slice-by-slice contouring





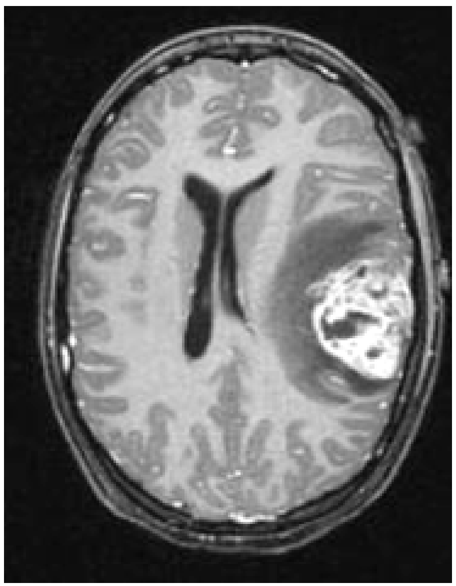
Demo itkSNAP tool

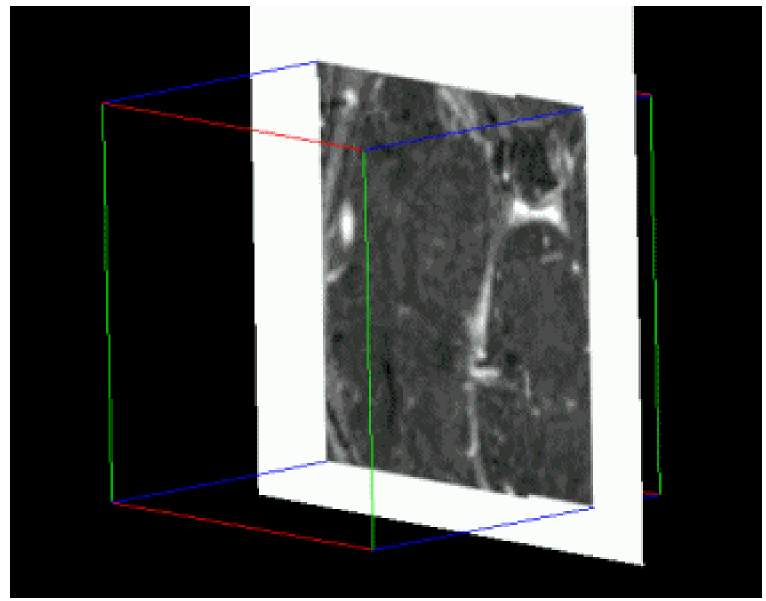


3D Geodesic Snake

Challenges:

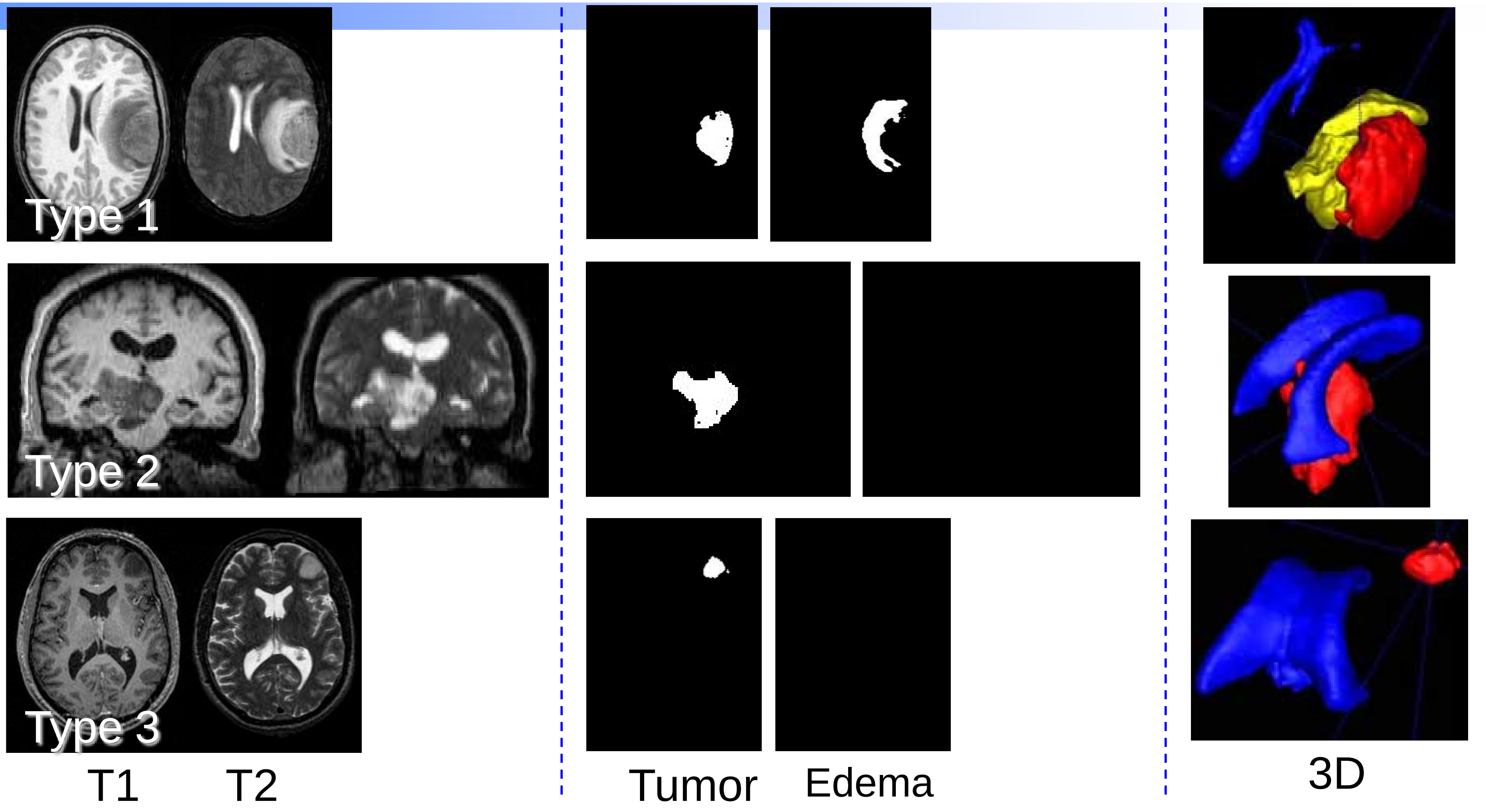
- efficient, stable 2D/3D implementation (implicit, fast marching,..)
- appropriate image match function to stop propagation





$$\frac{\partial \varphi}{\partial t} = (g)^{r_{MCF}+1} \nabla \cdot \left(\frac{\nabla \varphi}{|\nabla \varphi|} \right) |\nabla \varphi| + (g)^{r_{\nabla g}} (\nabla g) \cdot \nabla \varphi + (g)^{r_c} a |\nabla \varphi| + c_s \cdot (g)^{r_s} \nabla^2 \varphi$$

Results Brain Tumor Segmentation

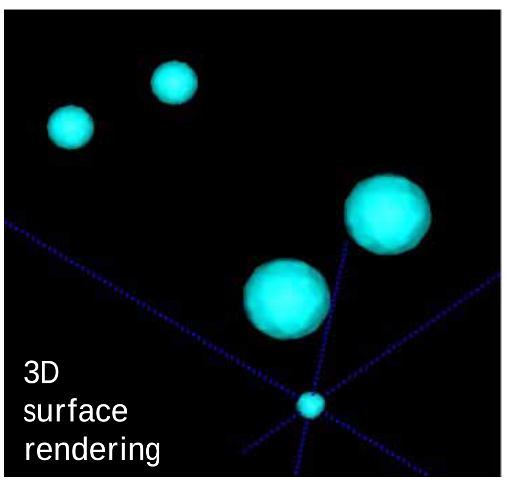


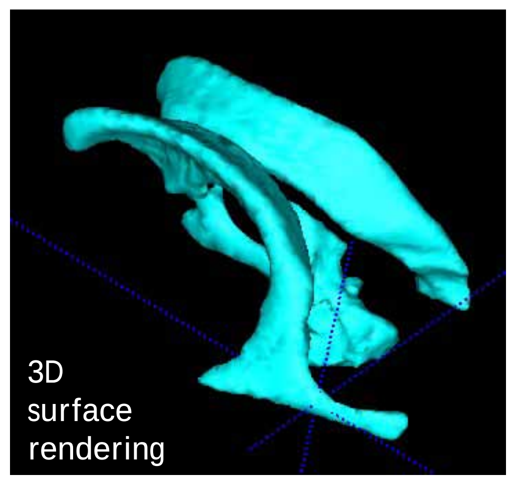
Prastawa et al., Media 2004

Ventricle Segmentation by 3D Snakes: UNC SNAP Tool

Initia-
lization
by
bubbles

Final
Segmen-
tation (10
seconds)



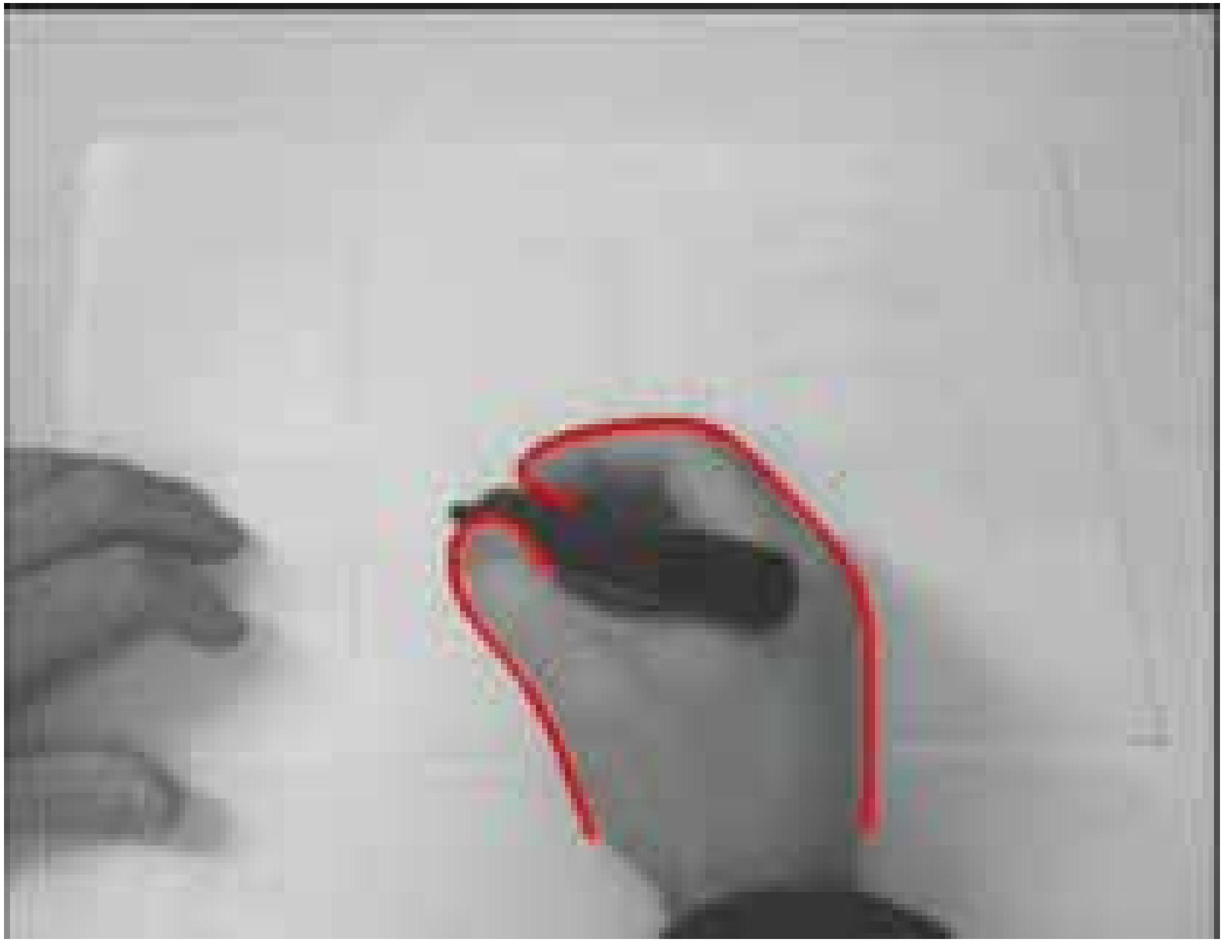


Reliability: 0.99

Efficiency: 2 Min

Download:
http://www.ia.unc.edu/dev

Use of deformable models in Vision I



Use of deformable models in Vision II

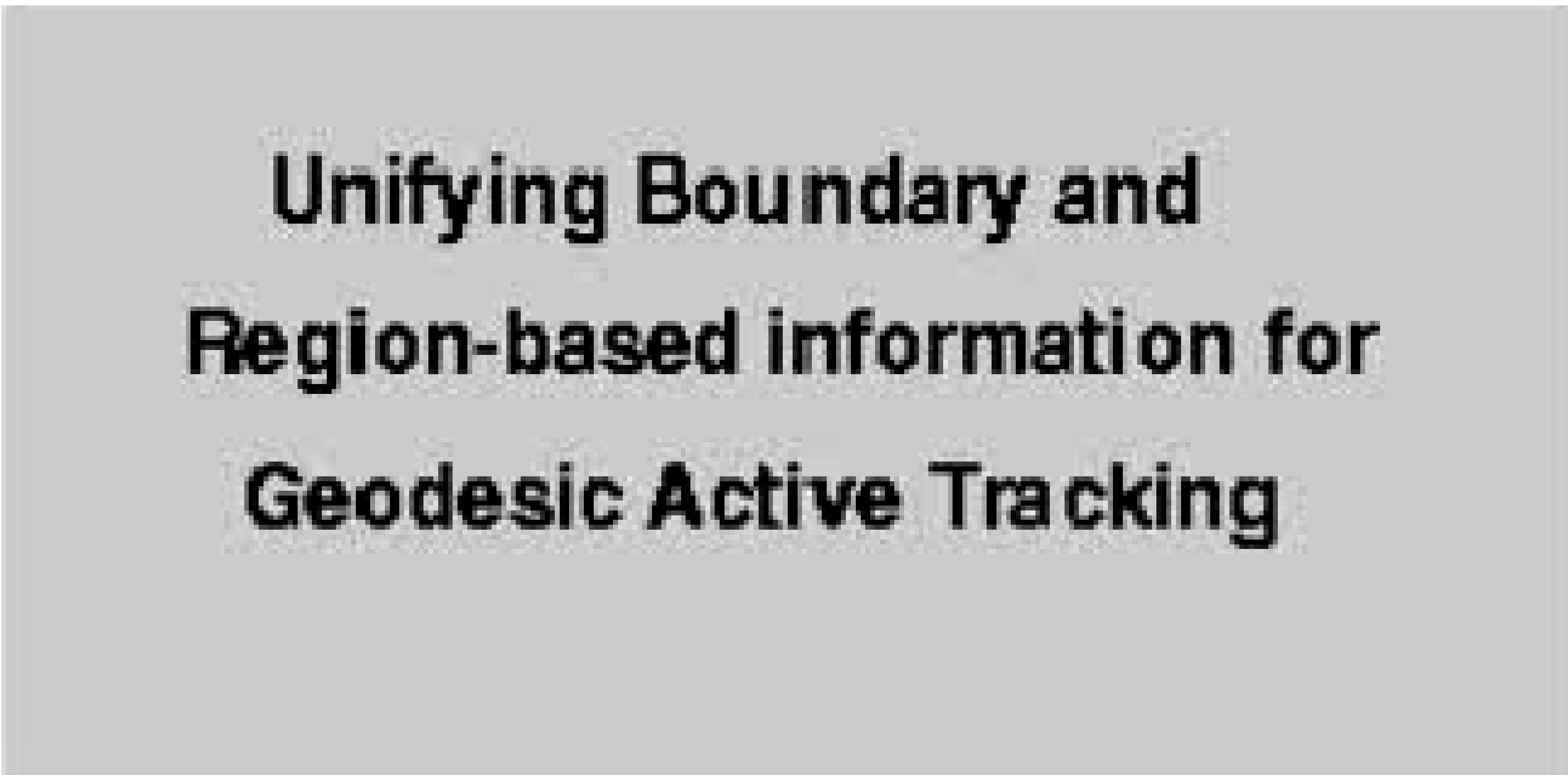
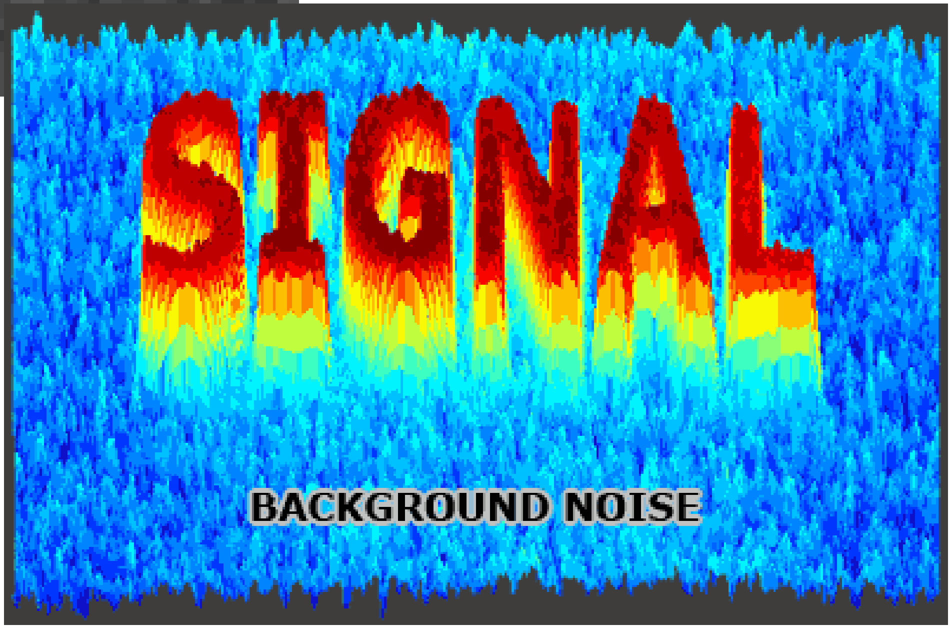


Image Noise



Blurring is diffusion

Linear isotropic diffusion, D is diffusion constant

$$\frac{\partial u}{\partial t} = div(D \cdot \nabla u) = \nabla(D \cdot \nabla u)$$

$$1-\dim : \frac{\partial u}{\partial t} = \frac{\partial}{\partial x}\left(D \cdot \frac{\partial u}{\partial x}\right)$$

$$D = const : u_t = D \cdot u_{xx}$$

Blurring of images

- Reduction of noise and small details
- Blurring is diffusion

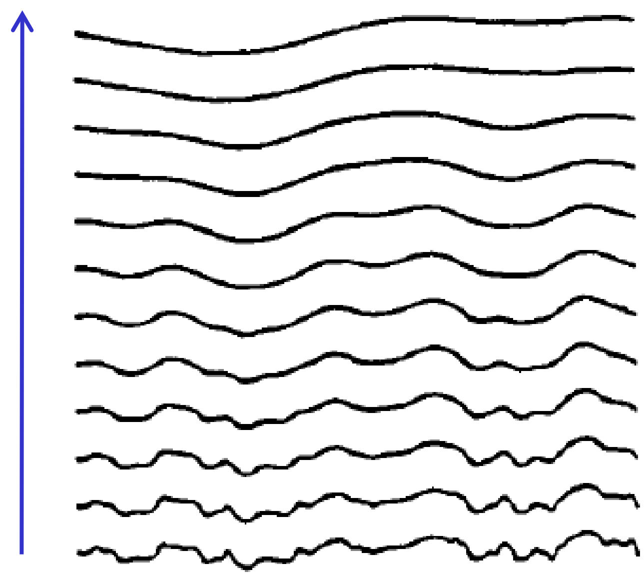
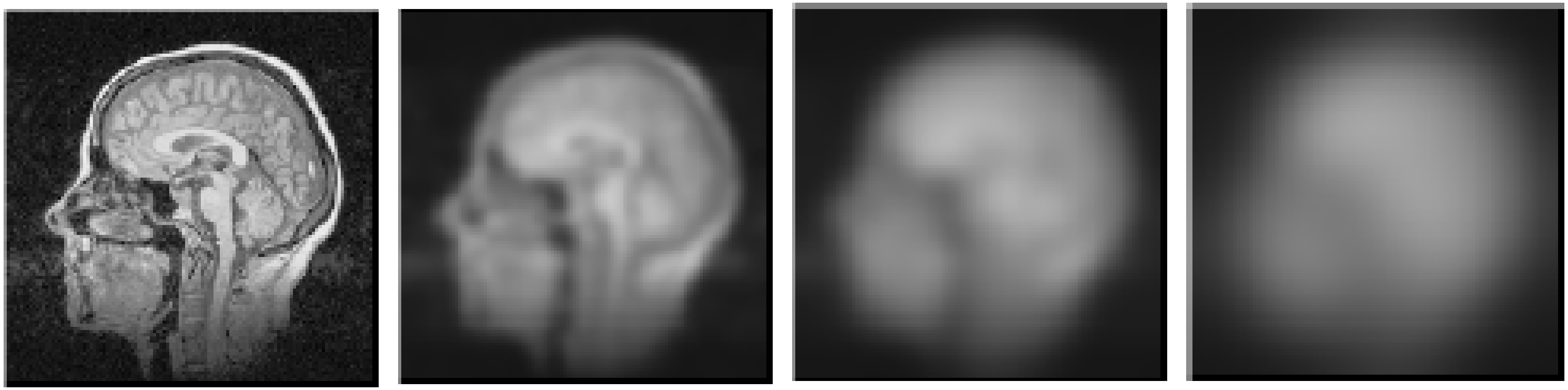


Fig. 1. A family of 1-D signals $I(x, t)$ obtained by convolving the original one (bottom) with Gaussian kernels whose variance increases from bottom to top (adapted from Witkin [21]).

Linear Diffusion

- Edge locations not preserved
- Region boundaries are preserved
- Gaussian blurring is local averaging operation and does not respect natural boundaries



Source: http://www.csee.wvu.edu/~tmcgraw/cs593spring2006/index.html

We want noise reduction while keeping structure boundaries

Trick: Diffusion constant D becomes locally adaptive:

D → D(x,t), i.e. D varies locally

e.g.: switch D to 0 near important image boundaries

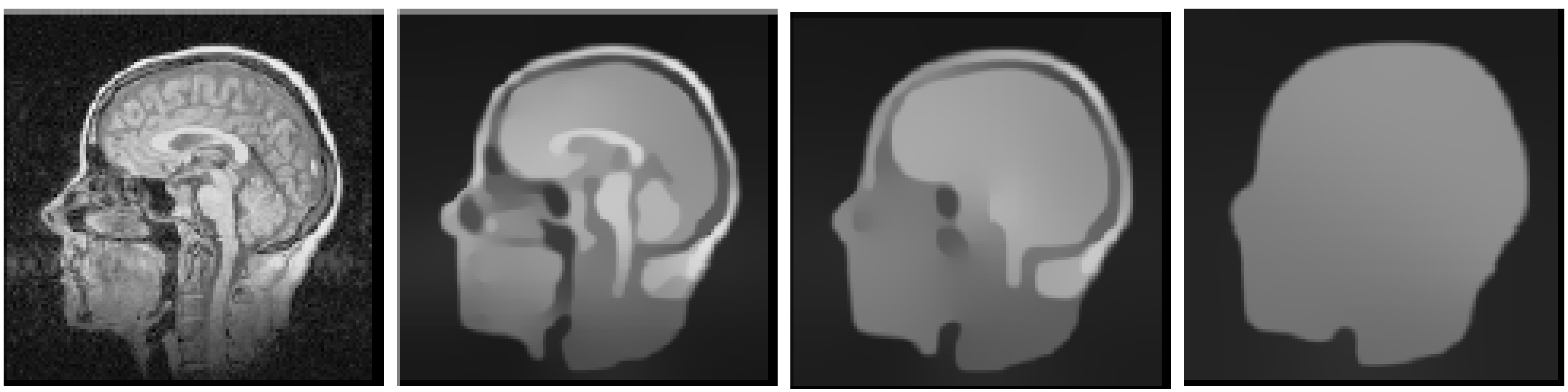
$$\partial_t u = \partial_x(\mathbf{D}(|\partial_x u|)\partial_x u)$$

DemoMathematica

Magic: This results in “inverse blurring”, or blurring with negative time, which is physically not possible.

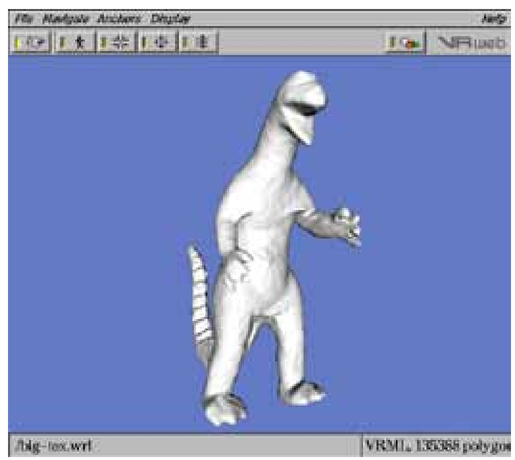
Nonlinear Diffusion

Multiscale image representation: Controlled blurring of structures by preserving wanted boundaries.



Source: http://www.csee.wvu.edu/~tmcgraw/cs593spring2006/index.html

Shape from silhouettes



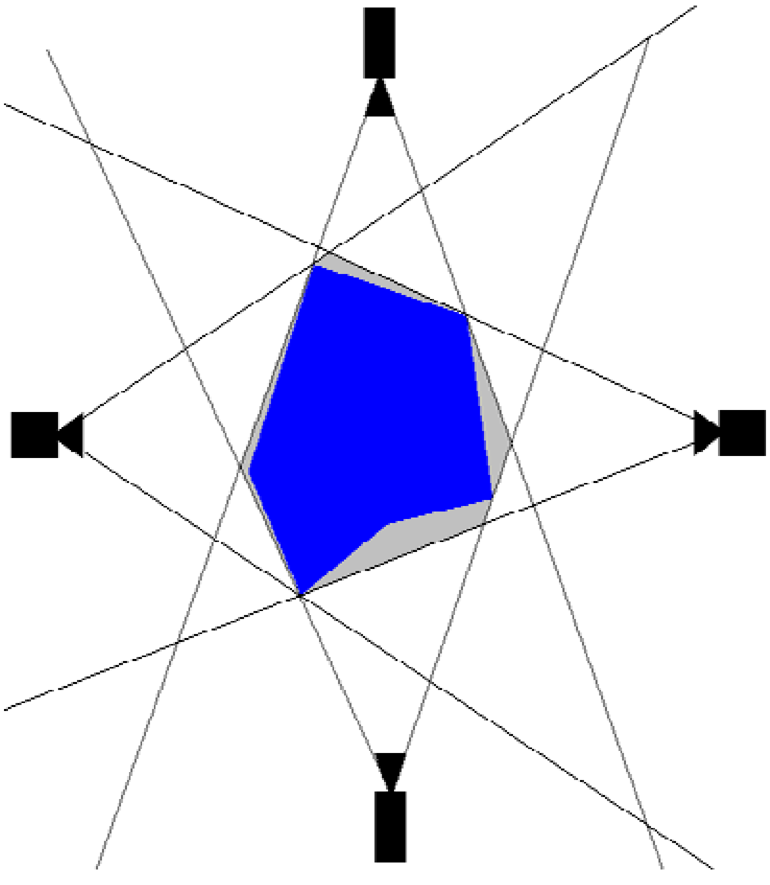
Slides from
Lazebnik,
Matusik
Yerex
and others

Automatic 3D Model Construction for Turn-Table Sequences, A.W. Fitzgibbon, G. Cross, and A. Zisserman, SMILE 1998

Motivation: Movies

Sinha Sudipta, UNC PhD 2008

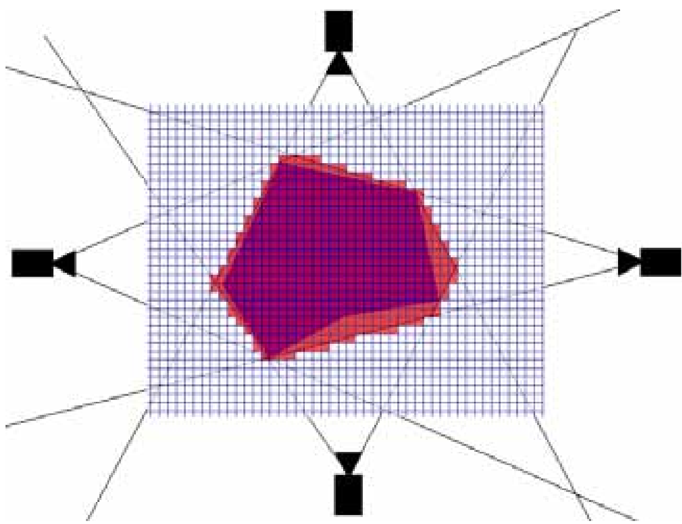
What is shape from silhouette?

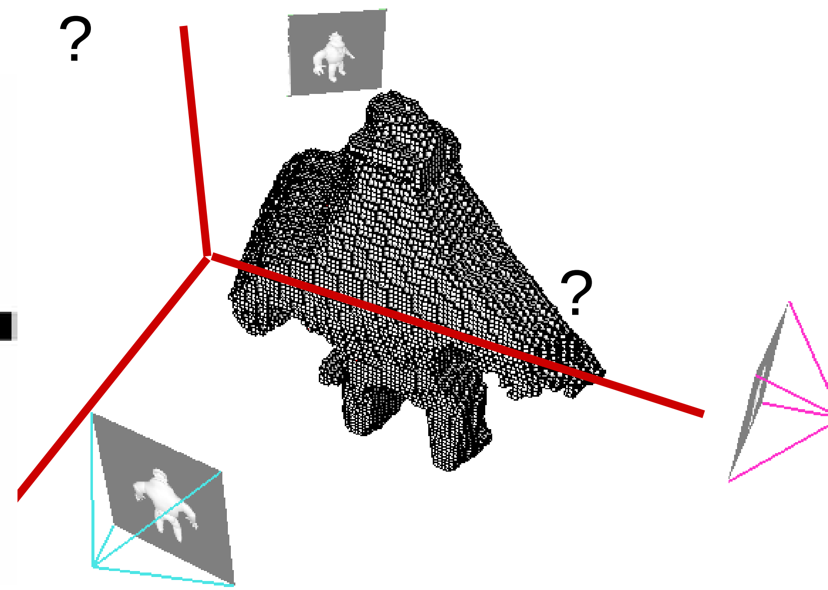


- With multiple views of the same object, we can intersect the *generalized cones* generated by each image, to build a volume which is guaranteed to contain the object.
- The limiting smallest volume obtainable in this way is known as the *visual hull* of the object.

Visual hull as voxel grid

- Identify *3D region* using voxel carving
  - does a given voxel project inside all silhouettes?

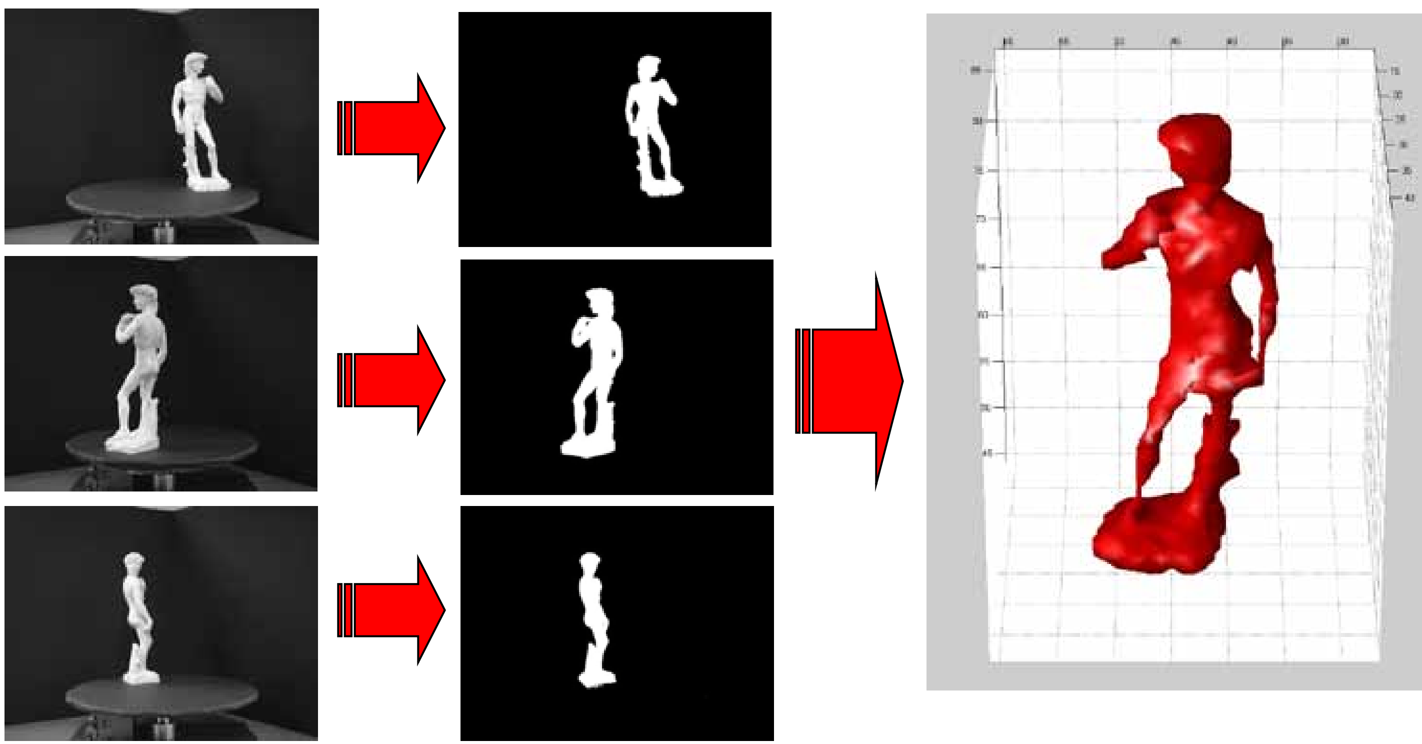




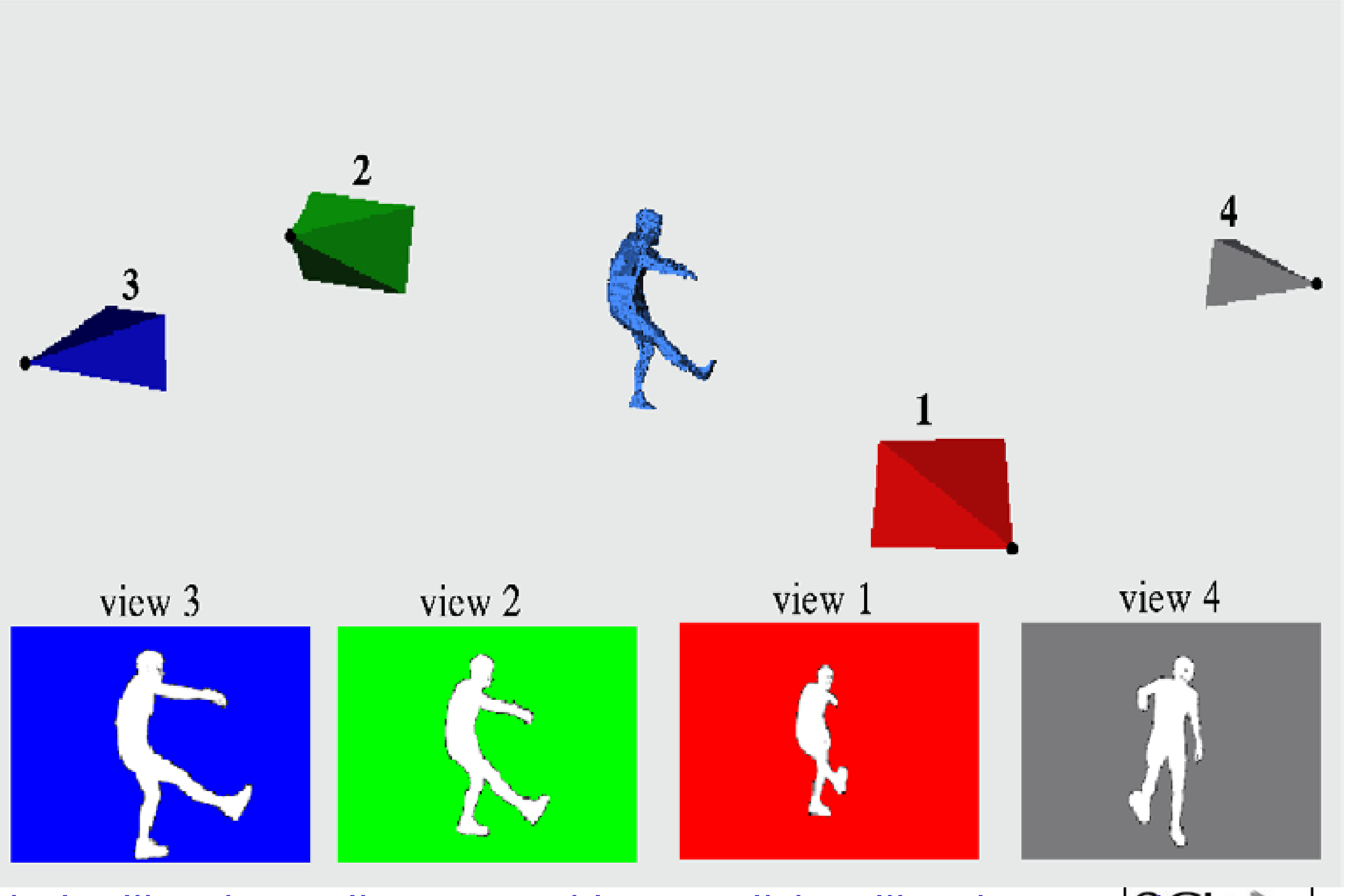
- pros: simplicity
- cons: bad precision/computation time tradeoff

Example Student Project

- Compute visual hull with silhouette images from multiple calibrated cameras
- Compute Silhouette Image
- Volumetric visual hull computation
- Display the result



Metric Cameras and Visual-Hull Reconstruction from 4 views

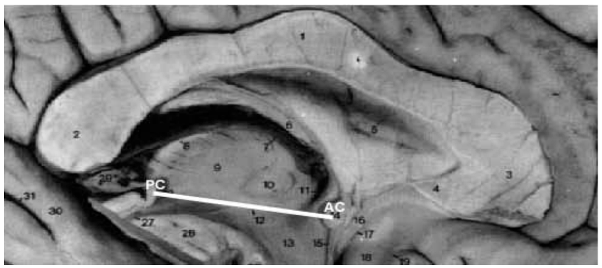


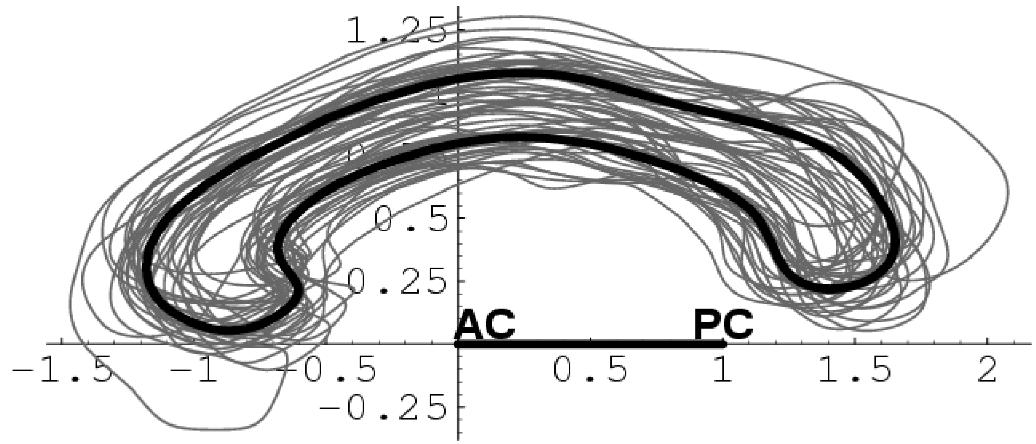
Final calibration quality comparable to explicit calibration procedure

Using probabilistic shape models

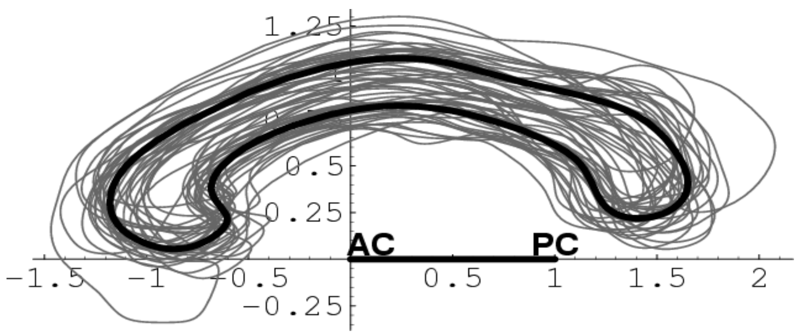
- Segmentation could be improved if we know the shape to be extracted.
- Idea: Using shape models:
  - Typical shape template -> Deformation
  - Statistical shape models -> Describe “shape space”, ensure that deformation stays within space of meaningful shapes

Natural Shape Variability



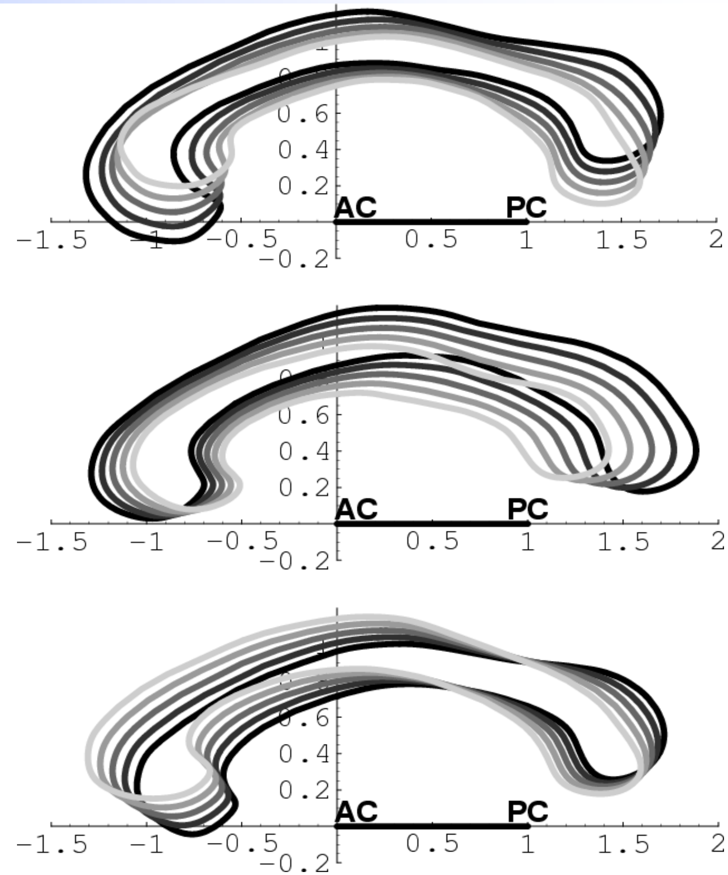


Notion of Shape Space



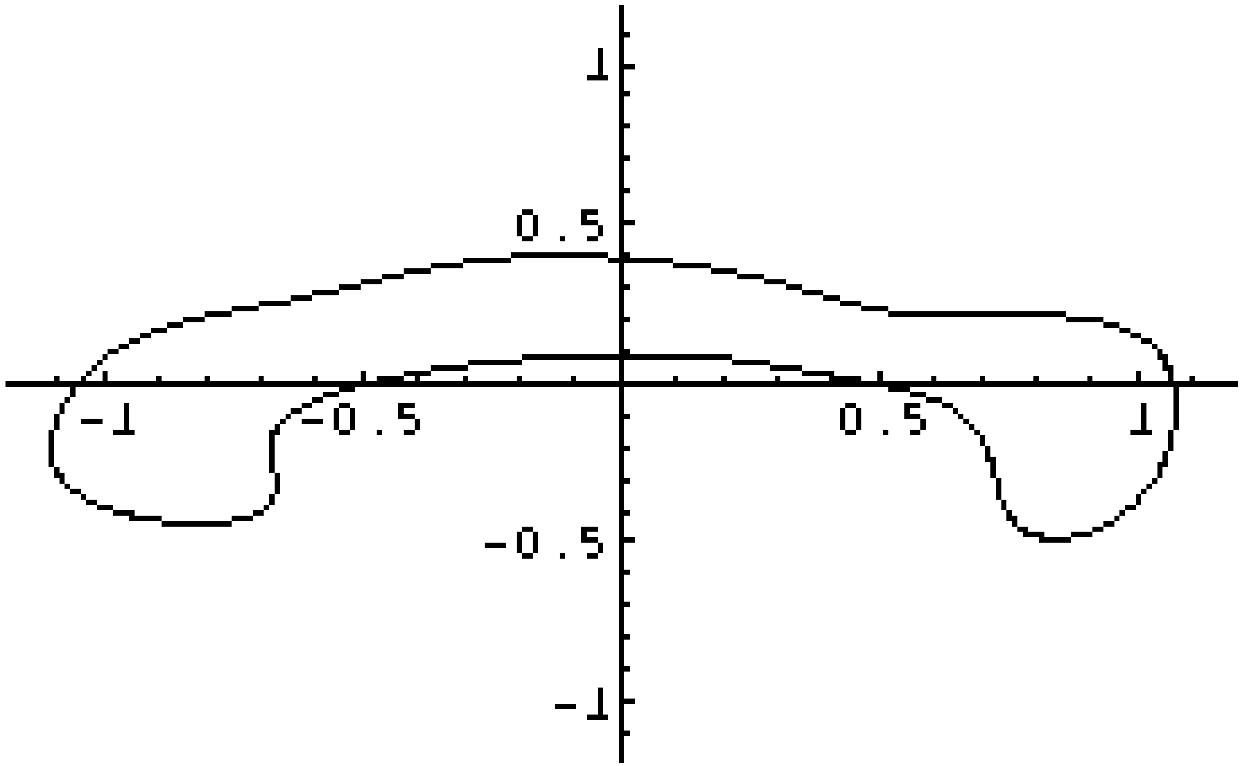
Outlines of the 71 corpora callosa (fine) and the computed average corpus callosum (bold).

Alignment
Parametrization (arc-length)
Principal component analysis
Þ Average and major deformation modes



The computed major modes of shape variation (top to bottom: modes 1,2 and 3).

First Eigenmode of Deformation (CC)



Segmentation by deformable models

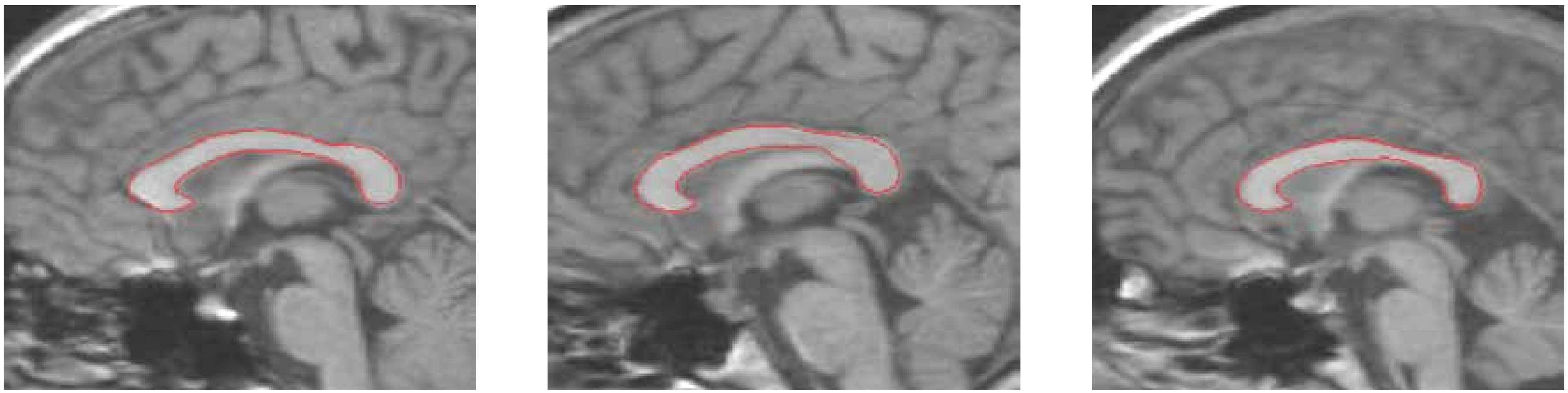
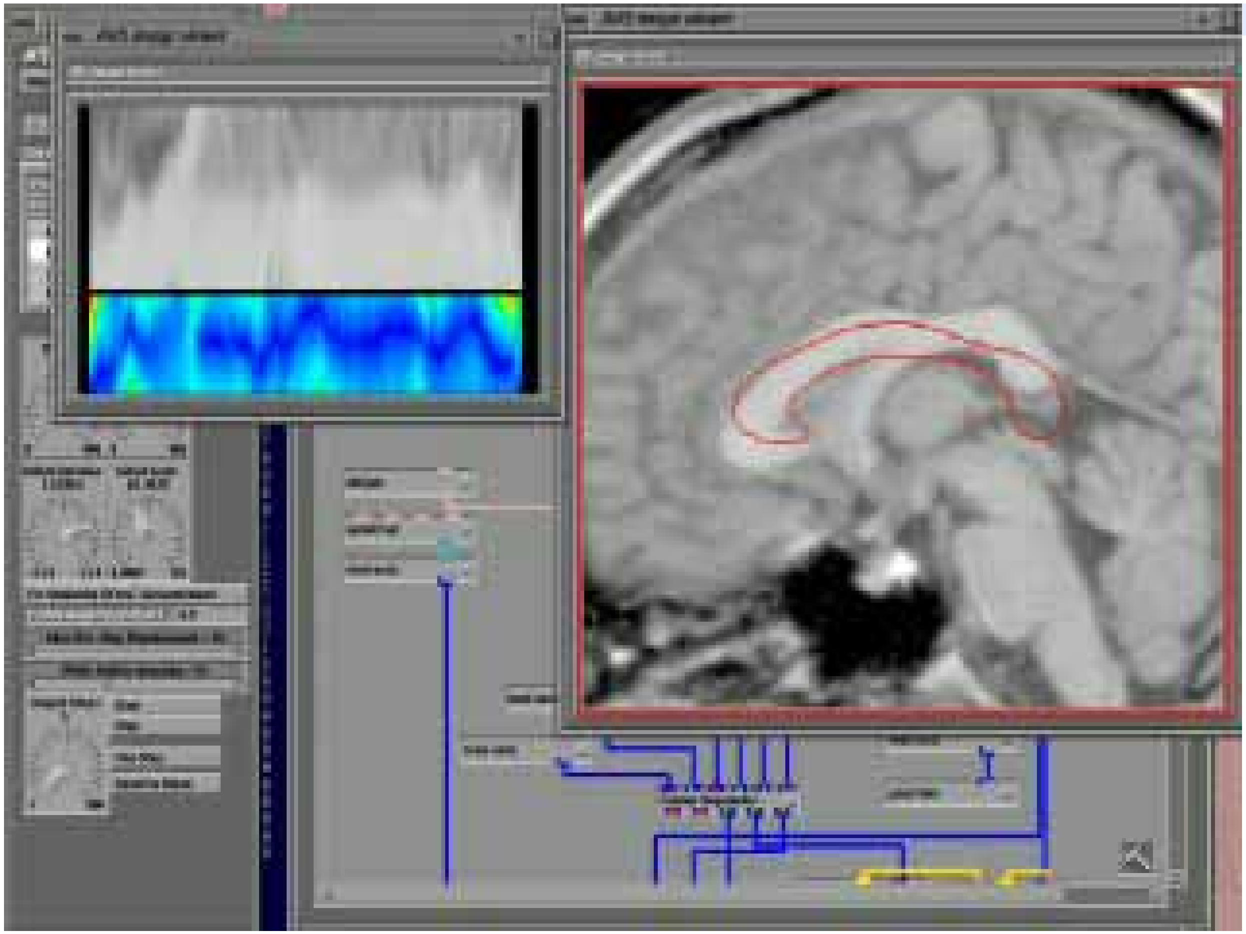


Fig. 1: Visualization of 3 MRI mid-hemispheric slices and the final positions (in red) of the automatic corpus callosum segmentation algorithm using deformable shape models.

Automatic deformable model based 2D segmentation



Example of model-based segmentation that uses a statistical shape model and a model of the boundary transition information.

Image Processing

- Input: Digital images
- Output: set of measurements, models, morphometric measurements, objects in abstract representation
- Key procedures:
  - Preprocessing, filtering, correction for artefacts
  - Geometric transformations (image registration)
  - Feature detection (edges, lines, homogeneous patches, texture)
  - Grouping of features to objects
  - Model-based versus data-driven segmentation
- Needs:
  - Math, Algorithms
  - Numerical implementations
- Excellent material: http://homepages.inf.ed.ac.uk/rbf/CVonline/

Why Image Analysis?

- Image Analysis and Computer Vision offer exciting research projects.
- Ideal area for CS (algorithms, math, coding, visualization, data structures …), ECE (robotics, pattern recognition, signal processing), BioEng (medical image analysis, and ME (robotics)
- Faculty at SCI from SoC, ECE, BioEng:
  - Ross Whitaker, Sarang Joshi, Guido Gerig, Tolga Tasdizen, Tom Fletcher, Marcel Prastawa, Rob MacCleod
- Weekly “ImageLunch” Seminar CS 7938: Mondays 12:15-1:25, WEB 3760 Evans and Sutherland Room
- **Main courses**: Image Processing (CS 6640, Fall), Computer Vision (CS 6320/6968, Spring), advanced courses

Next Lecture Thu Aug 25

- Read Preface and Chap 1 of the G&W book (pdf's on web-page).
- Get familiar with class web-page.
- Purchase class book.
- others