Erasmus MC
University Medical Center Rotterdam

Basics of Image Processing

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Erasmus MC – University Medical Center Rotterdam
Leiden University Medical Center
Delft University of Technology

New 3 year education programme

- Year 1: Image Segmentation
  - Methodology
  - Validation
- Year 2: Image registration and dynamic analysis
  - Methodology
  - Applications
  - Tracking
- Year 3: Quantitative imaging biomarkers (QIB)
  - Basics
  - QIB in neurological disease
  - QIB in cardiovascular disease

Image segmentation

- Introduction
- Image segmentation approaches
  - Pixel/voxel classification
  - Deformable model based segmentation
  - Active shape and appearance models
  - Atlas-based segmentation
- Validation and challenges

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Introduction

Non-invasive imaging

Röntgen' lab

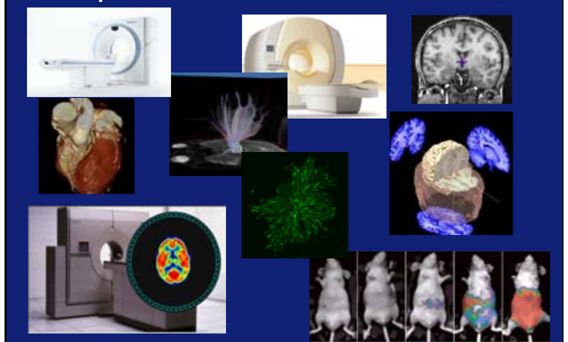
Wilhelm Conrad Röntgen

Discovery X-rays, 8 november 1895

First Nobel prize in Physics: 1901

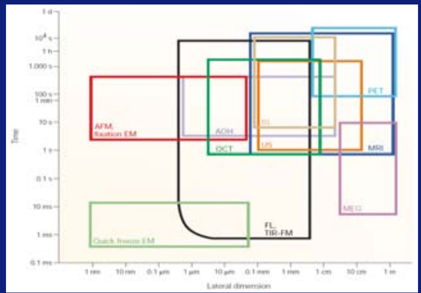
22 dec, 1895

We see brains "think", hearts beat, and follow processes to the molecular level



Many imaging modalities

- Imaging of complementary (bio)physical properties



R. Y. Tsien, Nature Cell Biology, 2003

Challenges

- Size and complexity of imaging data
- Multiple imaging modalities ➡ Data Explosion
- Multiple time points

How to enable

- Integrated visualization
- Quantitative image analysis
- Objectivity and reproducibility ➡ Automation
- Full exploitation of available information
- Development of imaging biomarkers

Computing tasks

- Image registration
- Image segmentation
- Tracking and motion analysis
- Quantitative image analysis
- Image visualization and fusion

Computing tasks

- Image registration
- ***Image segmentation***
- Tracking and motion analysis
- Quantitative image analysis
- Image visualization and fusion

Segmentation

- Define objects in a dataset in order to
  - distinguish relevant and irrelevant data
  - quantitative measurements
  - visualization

by

- manual outlining
- simple algorithms (thresholding)
- advanced (semi-)automated algorithms

Segmentation techniques

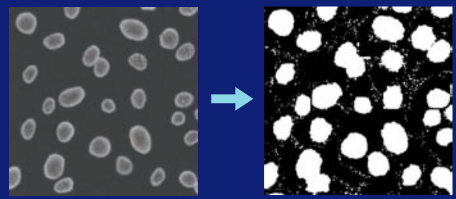
- "Low level"
  - ***Pixel/voxel classification***
    - Using intensities, gradients, texture
    - Grouping
- Model based
  - Including prior knowledge
    - Restricted parameterization
      - Imposed: ***Deformable models***
      - Learned: ***Active shape/appearance models***
        Atlas-based segmentation

Pixel classification

Simple example: thresholding

- Separating relevant structures from irrelevant background

Example of thresholding:



Supervised classification versus unsupervised clustering

- Unsupervised clustering

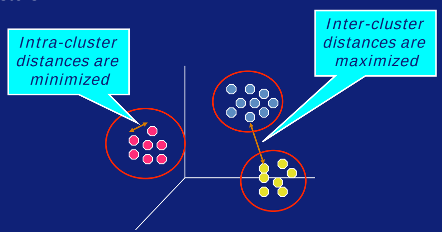
Group similar pixels together to form clusters
  - Minimize intra-class distance
  - Maximize inter-class distance

- Supervised classification:

Class label is available for training samples
  - Build model from training data
  - Predict voxel label unseen data using model

What is clustering?

- Form clusters of voxels such that they are similar (or related) to each other and different from voxels in other clusters



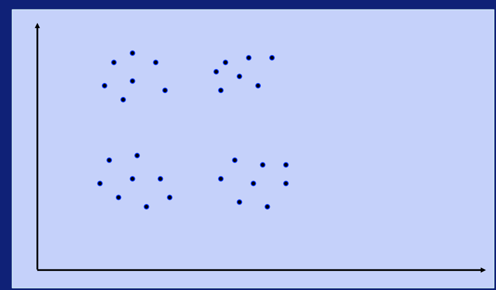
Overview of K-Means Clustering

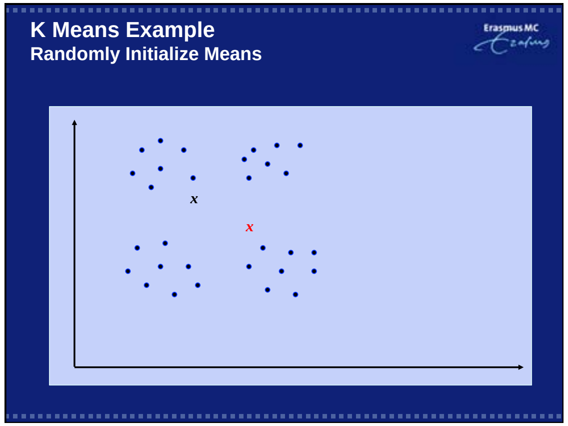
- K-Means is a partitional clustering algorithm based on iterative relocation that partitions a dataset into *K* clusters.

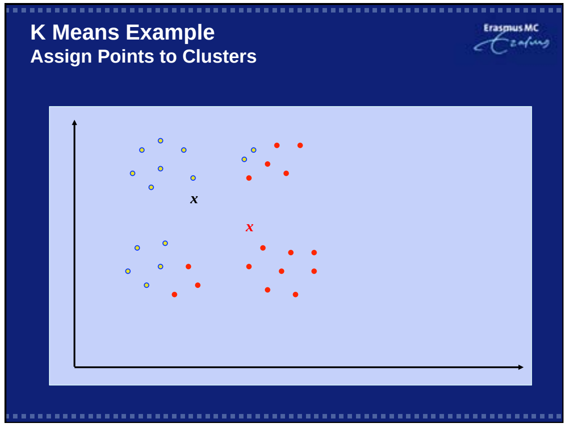
Algorithm:

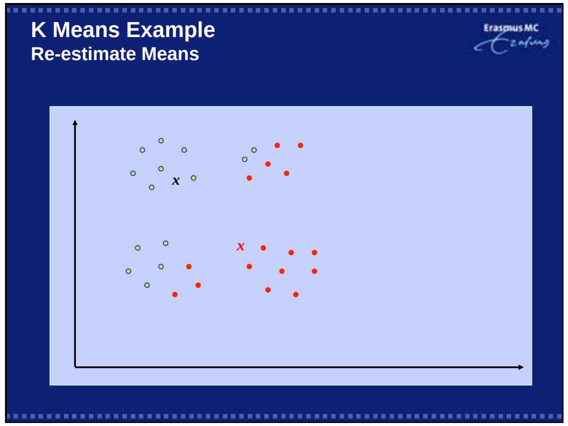
Initialize *K* cluster centers randomly. Repeat until *convergence:*
  - **Cluster Assignment Step**: Assign each data point to the nearest cluster
  - **Center Re-estimation Step**: Re-estimate each cluster center as the mean of the points in that cluster

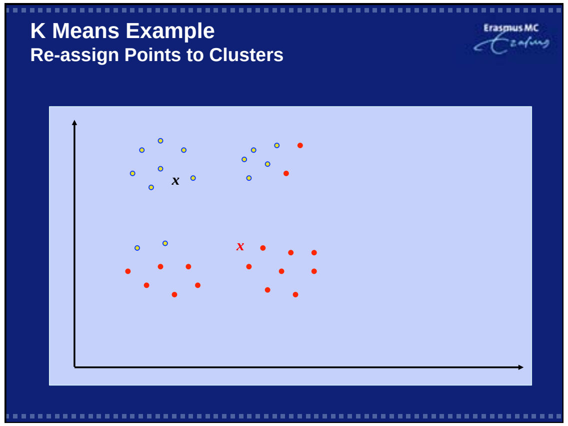
K Means Example

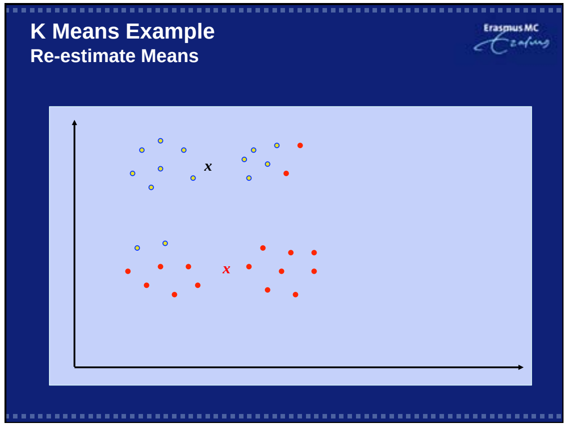


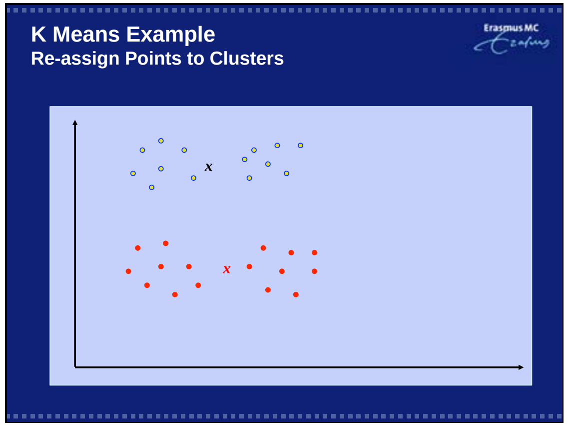

K Means Example
Randomly Initialize Means


K Means Example
Assign Points to Clusters

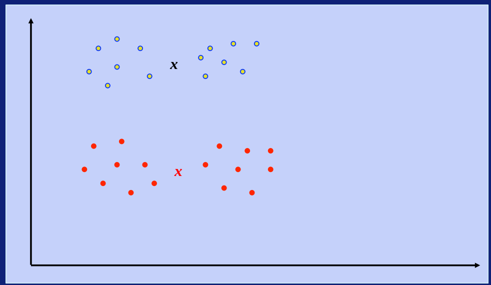

K Means Example
Re-estimate Means


K Means Example
Re-assign Points to Clusters


K Means Example
Re-estimate Means


K Means Example
Re-assign Points to Clusters

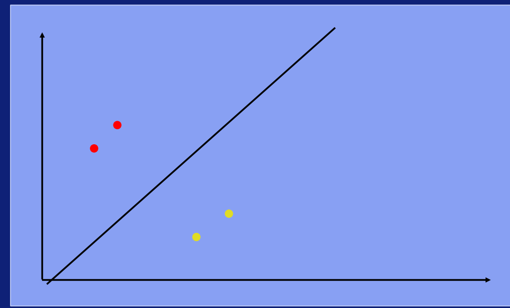
K Means Example
Re-estimate Means and Converge



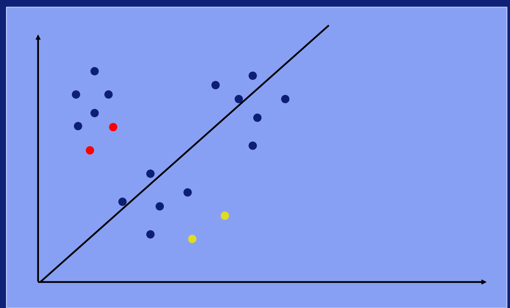
Many clustering algorithms

- K-Means
- Hierarchical clustering
- Graph based clustering (Spectral clustering)
- Bi-clustering

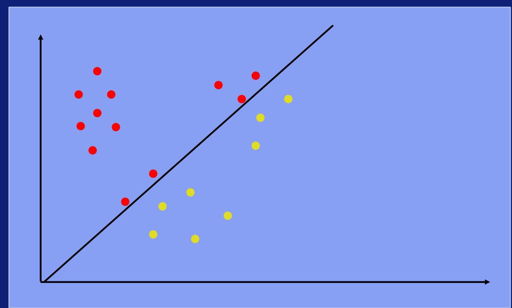
Supervised Classification Example



Supervised Classification Example



Supervised Classification Example

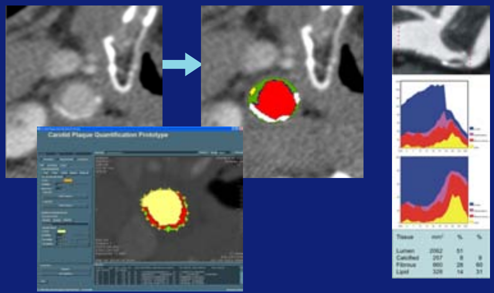


Classification algorithms

- K-Nearest-Neighbor classifiers
- Naïve Bayes classifier
- Linear Discriminant Analysis (LDA)
- Support Vector Machines (SVM)
- Logistic Regression
- Neural Networks

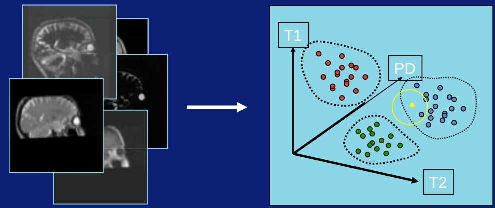
Quantification of atherosclerotic plaque

- Hounsfield unit based definition of plaque composition



Automated tissue segmentation

- Determining GM, WM, CSF volume as a function of age
- kNN based, with automated training



Automated segmentation grey/white matter, CSF, WML

Deformable model based segmentation

Snakes

- Introduced in 1988 (Kass, Terzopoulos, Witkin)
- Idea: a curve is fitted iteratively to the data based on
  - Image data
  - Curve shape

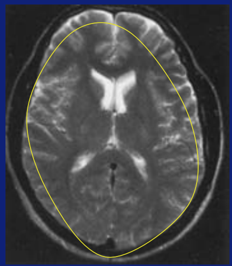
  until convergence
- "Active contour", "deformable model"
- In 3D surfaces

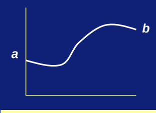
Example: Euclidean shortening flow

$$\frac{\partial C}{\partial t} = g(\kappa)\vec{N}$$

$$(g = \kappa)$$

Geodesics: shortest paths on a manifold





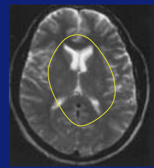
$$E(u) = \int_0^1 F(u, u_x)dx$$

$$u(0) = (a); u(1) = (b)$$

Snakes

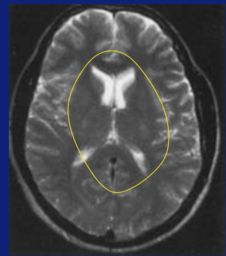
$$C(s) = (x(s), y(s))$$

$$E = \int_0^1 \left[E_{\text{int}}(C(s)) + E_{ext}(C(s))\right] ds$$



- E_{int} is the internal energy at all points of the snake
- E_{ext} is the external energy formed by the external forces attracting the curve
- Objective: Find the curve that minimizes the energy functional

Snake energy

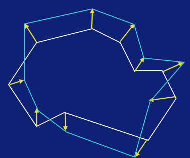


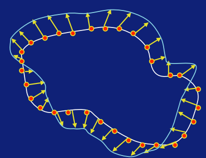
$$E_{\text{int}} = \omega_1 |C'(s)|^2 + \omega_2 |C''(s)|^2$$

$$E_{ext} = -\|\nabla I\|^2$$

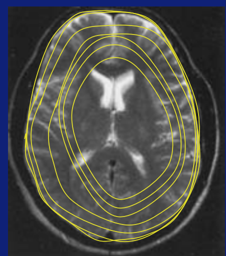
Representations

- Parametric active contour
  - Stored as vertices
  - Each vertex is moved iteratively
- Geometric active contour
  - Parameterization
  - Sampled at each iteration
  - Each sample is moved
  - New coefficients are computed (interpolation)





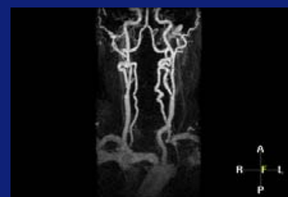
Snake algorithm



- For all points in snake
  - Sample a number of locations in the neighborhood
  - Select location with minimal energy
  - Repeat until convergence

Carotid imaging and analysis in 3D

- Automated artery segmentation and quantification



Better accuracy and reproducibility

Snake advantage

- Computationally efficient
- Flexible model, physically based
- Keeps initial shape (topology)

Snakes: disadvantages

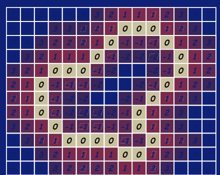
- Requires initialization close to the final solution
- May converge to local minimum
- Quite dependent on tuning parameters (weighting internal and external forces)
- Numerical instability (may oscillate)
- Keeps initial shape (topology)

Level set-based segmentation

Level sets: underlying idea

- Rather than evolving the curve/surface ***C(s)***, embed the curve as a level set in a one-dimensional higher image:
- E.g. $$U(\vec{x}) = \pm d$$

  where d is the distance to the ***C(s)***
- Evolve ***C(s)*** implicitly by evolving ***U(x)***



Speed function

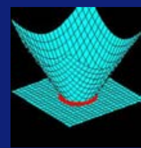
- Selected such that boundaries are captured
- Speed function only "makes sense" at the zero level set.
- Example speed function

$$g = \left[\frac{1}{1 - |\nabla I|^2 / k^2}\right]$$

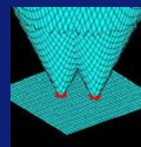
- Speed function can also be based on intensity, second order information, etc.

Level sets: change in topology

- Curves and surfaces are represented as level sets in a higher dimensional function



- This has important advantages:
  - Topological changes can be handled naturally

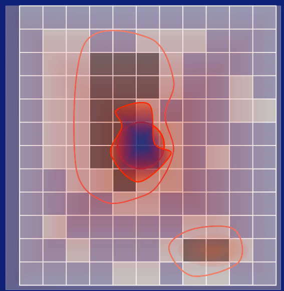


Example level set evolution

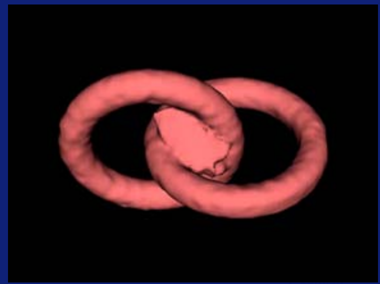
Segmentation with LS:
- Initialise the front C(0)
- Compute u(x,y,0)
- Iterate:

  $u(n+1) = u(n) + \Delta t g \|\nabla u\|$

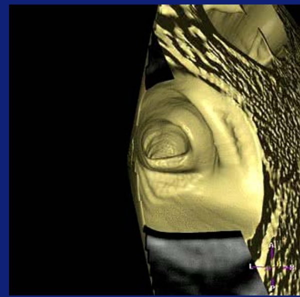
  until convergence
- Mark the front $u(t_{end})$



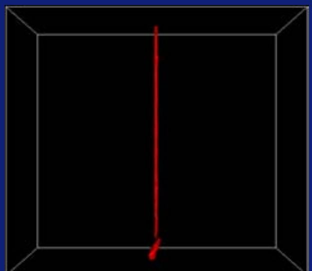
3D: Change of topology



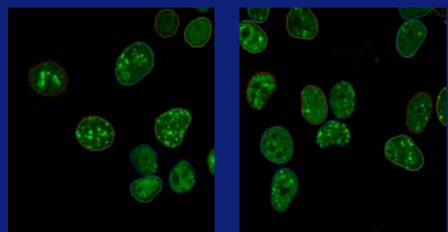
Applications



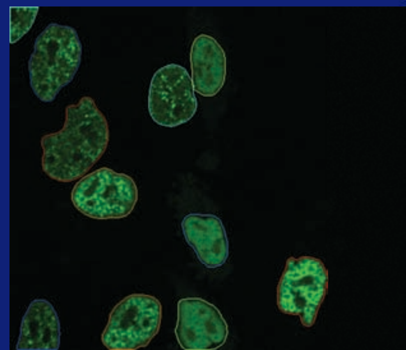
Extension to vascular data



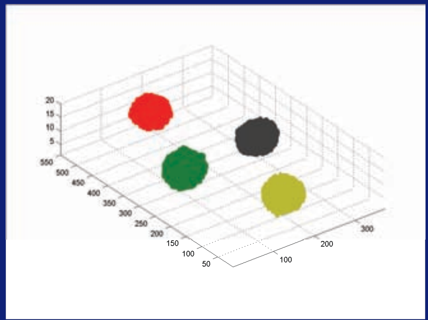
Cell tracking examples



Dzyubachyk et al. (2007)

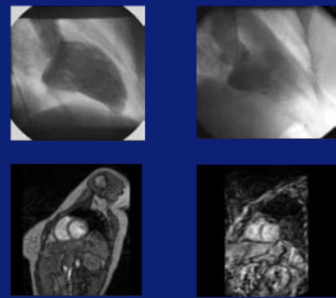


Embryogenesis C.elegans



Statistical shape and appearance models

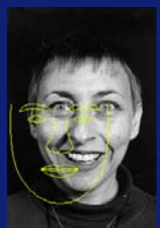
Active shape and appearance models: Integrating knowledge



AAM/ASM slides from Boudewijn Lelieveldt, LUMC Leiden

Active Shape Models

- Introduced by Cootes and Taylor
- Matching local appearance

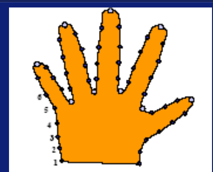


Movies: Tim Cootes

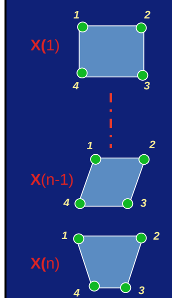
Point distribution models

- Acquire manually drawn contours
- Define landmarks
- Define denser point correspondence

Cootes et al.



ASM construction: 2D example



- Shapes are represented by a vector of "landmarks" and their connectivity

$$\mathbf{x} = \{P1, P2, P3, P4\}^T$$

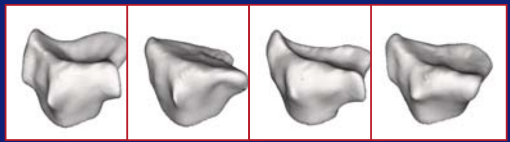
- The mean shape is the average vector

$$\bar{\mathbf{x}} = \frac{1}{n}\sum_{i=1}^{n}\mathbf{x}(i)$$

- Variability is computed by PCA of the covariance

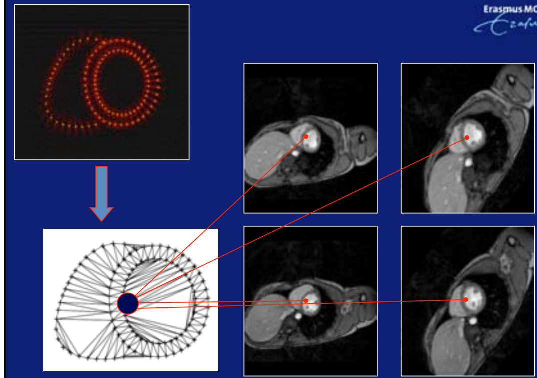
$$\mathbf{S} = \frac{1}{n-1}\sum_{i=1}^{n}(\mathbf{x}(i)-\bar{\mathbf{x}})(\mathbf{x}(i)-\bar{\mathbf{x}})^T$$

Natural variation can be modeled

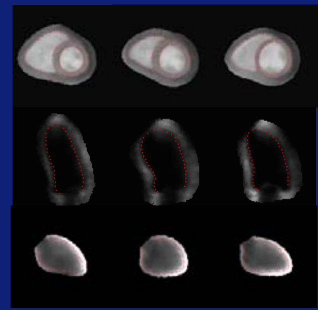


1st Mode *2nd Mode* *3rd Mode* *4th Mode*

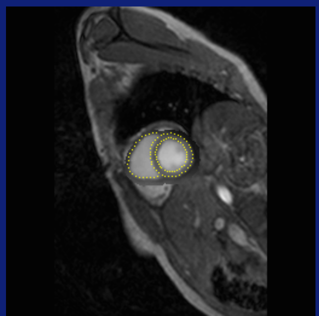
Each mode is varied between –5σ and +5σ



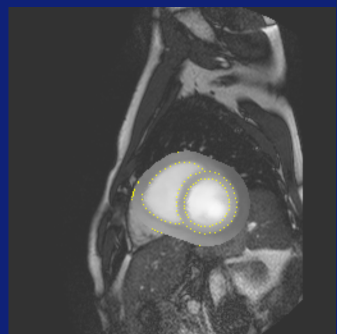
Intensity / shape modeling



Matching examples: cardiac MR



Matching examples: cardiac MR

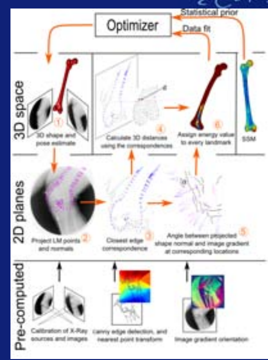


Shape model fitting

Energy optimization, based on edges and orientation

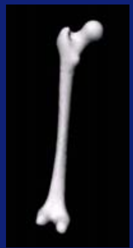
Two-stage approach:

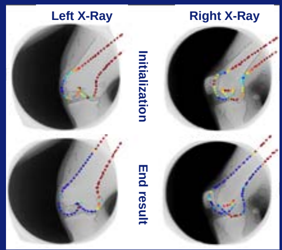
1. Pose estimation with mean shape
2. Simultaneous pose and shape optimization



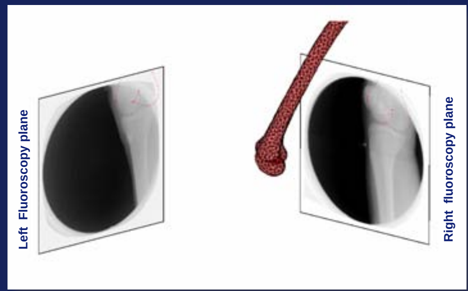
3D shape reconstruction

3D statistical shape model fitting to the Canny edge-map, and automatic selection of the relevant bony edges





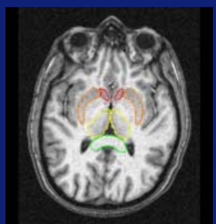
3D femur reconstruction from biplane fluoroscopy

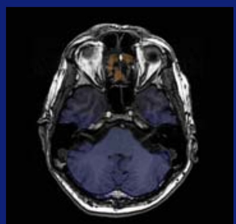


Atlas-based segmentation

Atlas-based segmentation of individual neurostructures

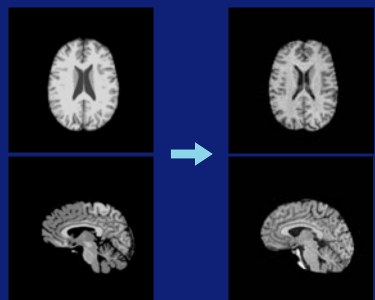
- Segmentation of multiple neurostructures



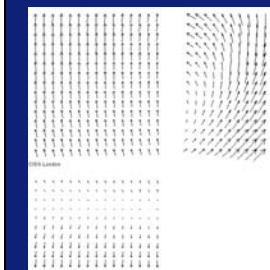


Labeled atlases

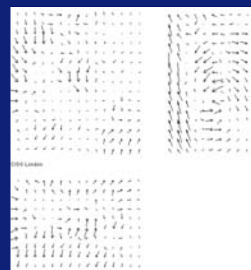
Intersubject nonrigid registration



Underlying deformation

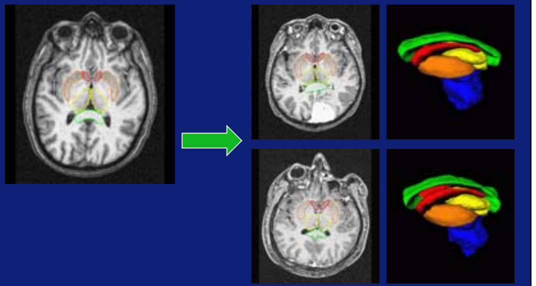


Affine component



Nonrigid component

Atlas Mapping



Courtesy: Medtronic

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Anything You Can Do, I Can Do Better (No You Can't)... *

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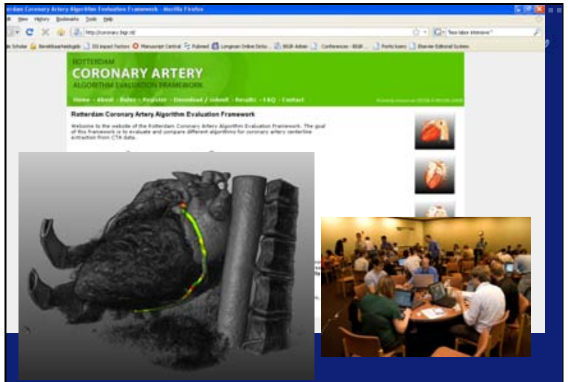
Don't assume, assess!



Carotid Bifurcation Algorithm Evaluation Framework

Average lumen measures

Method name	Automatic	Total success	dice		mad		max		Total
			%	rank	mm	rank	mm	rank	rank
Reference		41	100.0	1.00	0.01	1.00	0.05	1.00	1.00
ObserverA		41	95.1	2.61	0.10	2.68	0.54	2.85	2.72
ObserverB		41	94.6	3.34	0.11	3.37	0.62	2.93	3.21
ObserverC		41	94.4	3.46	0.12	3.32	0.72	3.85	3.55
SCR_Gulsun_Tek Gülsün and Tek		41	91.8	5.95	0.18	5.68	1.11	5.32	5.65
GIMET Krissian and Garcia		41	87.3	6.05	0.54	7.02	2.98	7.05	6.71
Medisys Cuisenaire	X	33	89.6	8.05	0.17	6.90	1.11	6.83	7.26
TubularAnisotropy Mille et al.		41	83.5	8.66	0.74	8.68	6.06	8.80	8.72
HUJI-CASMIP Freiman et al.		41	82.9	8.85	0.75	9.05	5.64	8.85	8.92
MARACAS Zuluaga et al.		41	80.9	9.63	0.82	9.68	5.96	9.39	9.57
media Wong et al.		41	77.5	9.34	1.10	9.73	7.32	10.10	9.72
RGC Valencia et al.		37	53.6	11.07	3.39	10.90	9.10	11.05	11.01

Summary

- Segmentation techniques vary in the way they model the object to be segmented, and the a priori information that is included in the algorithm
- Voxel classification: - supervised versus non-supervised
  - simple to complex image features
- Deformable models add smoothness constraint
  - Level sets allow for topological changes
- Active shape and appearance models constrain shape based on examples, and learn appearance
- Atlas-based methods employ registration (covered in detail next year ☺)