Segmentation of medical images

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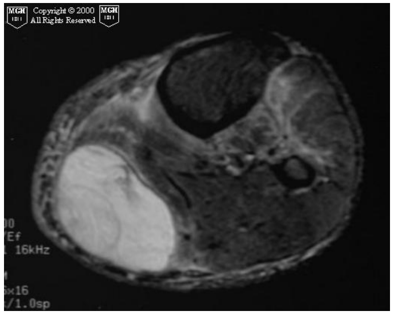
Overview

- Medical images
- Segmentation issues and taxonomy of methods
- Algorithms
  - Voxel based: color/feature clustering
  - Regionalization
  - Contour/surface based
    - Locally constrained
  - Atlas based
    - Global constraints
    - Segmentation and registration

Medical images

- Different modalities acquiring different physical values
    - Morphological
        - CT, MRI, CR, US...
    - Functional
        - FMRI, PET, SPECT
- Relevant noise
- Artifacts
    - e.g. Partial volume, Beam Hardening in CT

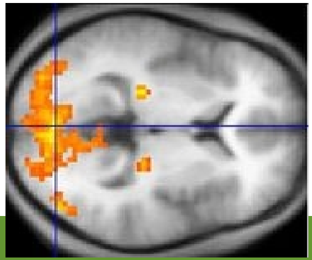
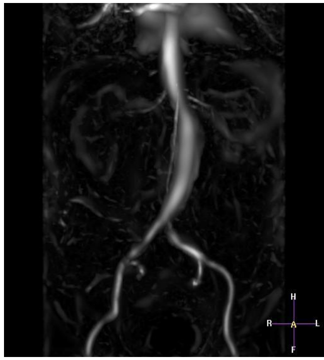
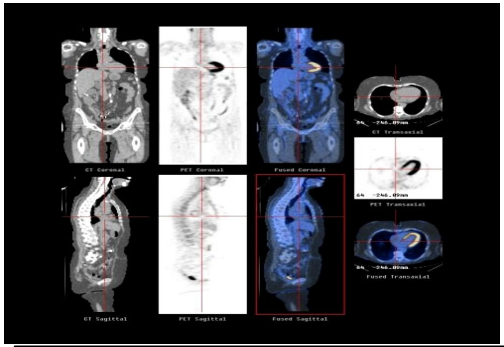


Image processing

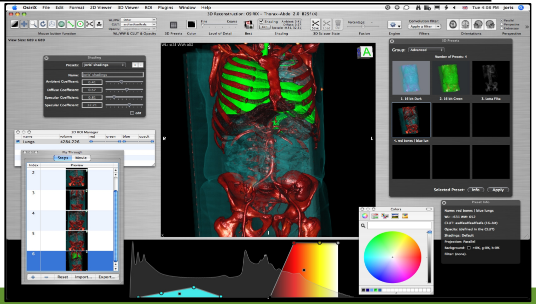
- Input: image(s)
- Output: image(s)
- Algorithms used for
  - Noise removal
  - Artefacts removal
  - Contour enhancement
  - Vessel enhancement
  - Support for visualization
  - Image registration/fusion



From. T. Deschamps



From GE Healthcare



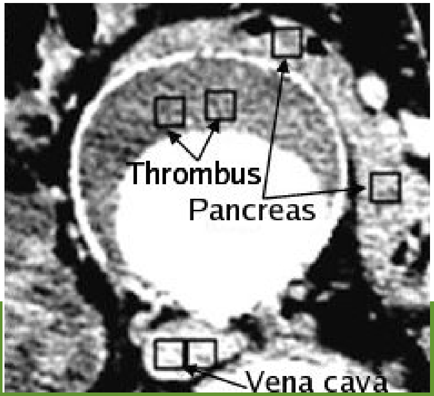
From Osirix

Segmentation

- Image understanding, vision task
- Input: images
- Output: Reconstruction/interpretation
  - Pixel/voxel labelling
  - A 2D/3D/4D "scene" reconstruction
  - The **"virtual" anatomy** we are interested in
  - Further information may be obtained
    - Functional data (functional imaging, motion)
    - Texture classification (diagnostic info)

Segmentation of medical images

- Usually 3D 4D image stacks spatially referenced
- No geometric reconstruction problems as in classical computer vision
- Relevant problems:
  - Noise (low S/N ratio)
  - Poor color - texture characterization: different organs may appear similar in medical images
  - Typical imaging artefacts
  - Validation is mandatory



Taxonomy of methods

- Manual, computer assisted
  - Drawing interface (intelligent scissors, snakes)
  - Seed placement (region growing, s-t graph cut...)
  - Parameter tuning
- Completely automatic
  - Voxel labelling
  - Model registration

Based on output data

- Voxel labels
  - Without spatial relations
    - Thresholding, Supervised labeling, clustering
  - Connected components
    - Watersheds, Region growing, split and merge, graph cut, optimum partitioning
- Contour/surface representations
  - Unstructured
    - Edge detection, Isosurfaces (Marching Cubes)
  - Structured
    - Active contours (topologically constrained)
    - Level set, Active Shape models, model fitting, ecc.

Data structures

- For Human simulation purposes we need a reliable organ representation, i.e. a reliable volume partition in meaningful connected components
- Then we can easily move from voxelized, surface mesh or volume mesh representation

Based on prior information

- Bottom up
  - Pixel voxel based
    - Noise removal, feature extraction
    - Classification, clustering, region growing...
- Top down
  - Use of a priori information on what we are looking for
    - Model fitting
    - Model registration
- Intermediate
  - Use of local constraints (neighbourhood, contour-based...)

Bottom up/Top down

- Critical choice
- Bottom up
  - Segmentation only depend on voxel features
  - Image information is maximally preserved
  - But makes difficult to obtain a virtual organ model
- Top down
  - Models should be accurate
  - Difficult to capture anomalous shapes
- Hybrid approaches can be used
  - A priori hypotheses with increasing strength can be exploited

Common algorithms

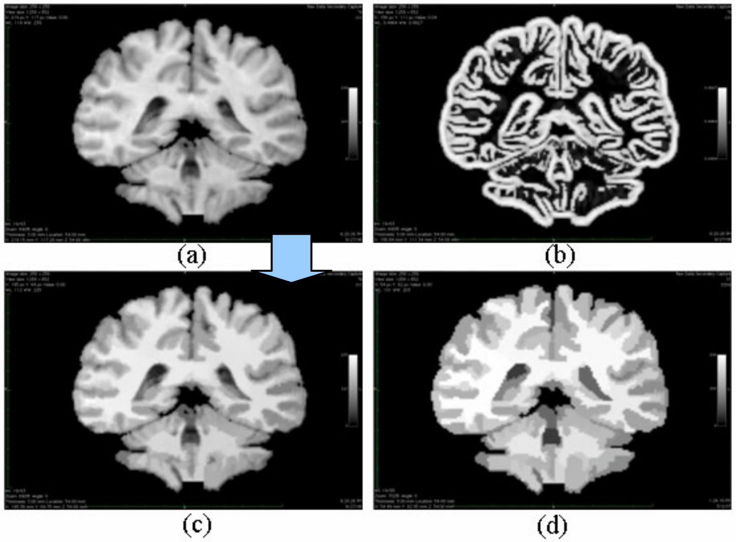
- Classification/clustering in color/feature space (pixel, voxel based)
  - Regionalization methods, binary region processing
- Graph based methods
  - Use of information about pixel/voxel neighborhoods
- Contour/surface based methods
  - Use of (weak) constraints and a priori assumptions on regions to be extracted
- Model based approaches
  - Use of strong constraints on organ shapes
  - “Registration” tecniques

A bottom up approach

- Pixel-Voxel labelling
- Classify voxels according to local features (intensity, vector/tensor components, edges, etc.
- A priori hypotheses: may be just number of cluster, or thresholding values
- Simple thresholding is a particular case
- But more complex/automatic approaches are continuously proposed

Voxel based methods

- Supervised learning methods, e.g. Bayesian classifiers
  - Use of histogram information on a training set
- Unsupervised clustering
  - K-means, mean shift...
- Widely used
- Do not provide directly a regionalization. Post Processing required
  - e.g. morphological processi..g,
  - Region growing, merging



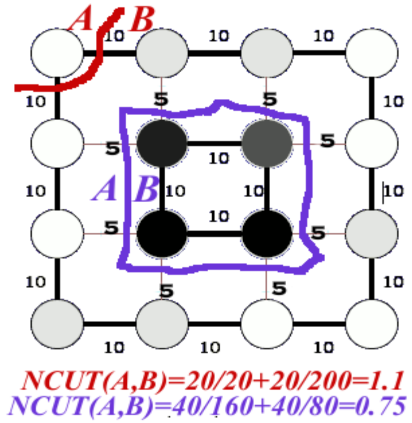
Plugin for OsiriX: Mean Shift Segmentation
Vides Cañas S., Azpíroz Leehan J

Adding constraints

- Add a regionalization method to clustering rules
  - e.g. region growing, split and merge, watershed transform
- Modify label probability according to local neighborhood:
  - Markov Random Fields approach
- Graph Theoretic Clustering
  - Minimum weight cut, Normalized cuts, S-T cuts

Graph cuts

- Image as a Graph
  - Voxel as nodes
  - Neighbors are connected
  - Connections weighted by similarity



- Find optimal partition in meaningful regions
  - Minimizing the weight of the cut
  - Normalized to avoid small regions (Shi and Malik '00), computationally complex
  - Seeded with external nodes (Boykov-Kolmogorov '01), user dependent

Contour based approach

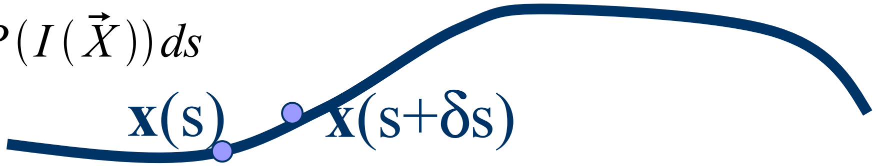
- Active, Deformable Contour/Surfaces Approach
  - Define a curve/surface including the interesting region
  - Make it attracted by the region boundaries
- Add “local” shape constraints contour/surface continuity, regularity, etc
- Use only (with exceptions) boundary information
  - Efficient, problems with initialization/

Active contours/surfaces

- Two different approaches
  - Explicit, parametric
    - Define a parametric data structure defining the curve/surface (i.e. point chain, surface mesh) and define a dynamic depending on local shape and image properties
    - Topologically constrained, efficient implementation
  - Implicit, geometric
    - The curve/surface is defined as the zero level of a scalar function of higher dimensionality
    - Can change topology, complex

Evolution of algorithms

$$E = E_C + E_{imm} = \alpha \int_0^1 \left| \frac{\partial X}{\partial s} \right|^2 ds + \beta \int_0^1 \left| \frac{\partial^2 X}{\partial s^2} \right|^2 ds + \int_0^1 P(I(\vec{X}))\, ds$$

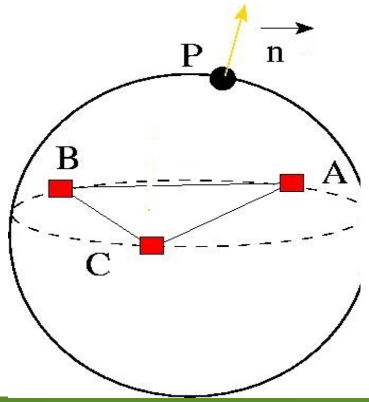


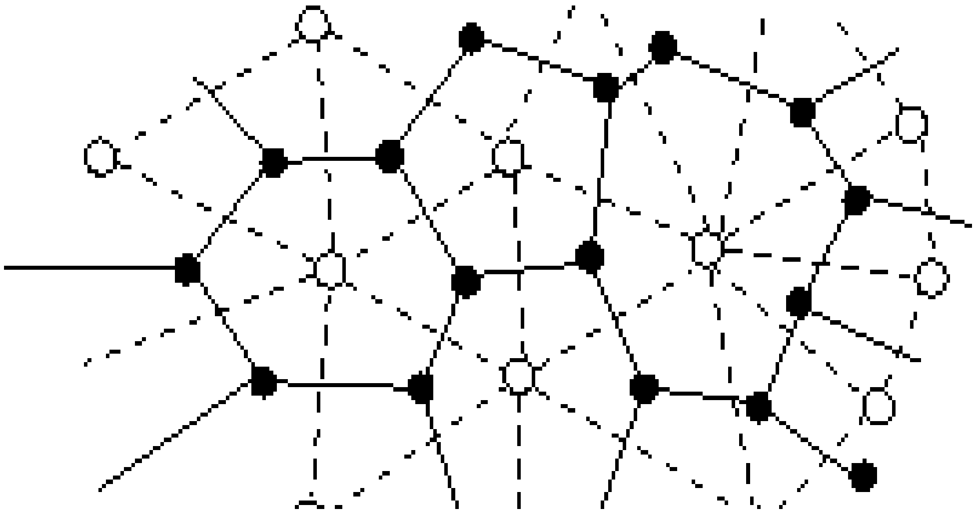
- Snakes (Kass et al. '87)
  - Contour attracted by edges, and constrained keeping the curve smooth
  - Need initialization close to the boundaries
  - Tricks to have easier initialization: Balloon models (a force inflating the contour, Cohen and Cohen 91, Gradient Vector Flow, Xu and Prince)
  - Tricks to handle topology changes

3D extension

- Need a data structure making easy to control local average curvature
- 2 - Simplex Meshes (Delingette'94)
  - Meshes where nodes are connected with 3 neigbors
  - Easy to compute

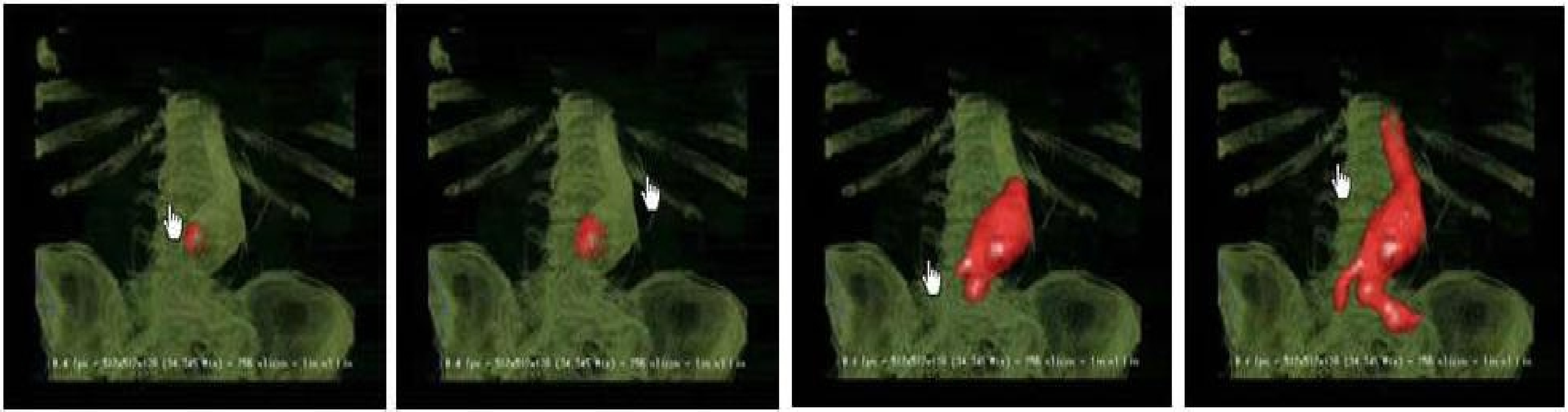
  average curvature





Example

- Growth from a small sphere
- Automatic reparametrization



Evolution of algorithms

- Implicit methods: Level sets (Malladi 94, Caselles'92)
  - Define a contour, define a speed on the contour perpendicular to the curve and image dependent, the implicit function, and evolve it
  - Complex and tricky, but fast approximated method
  - Handles naturally topology changes

Evolution of algorithms

- Geodesic Active Contours (Caselles '97):
  - A simplified snakes algorithm (with contour elasticity) can be implemented in the LS framework
- Region driven methods
  - Active contours depend only on boundary information and not on region homogenity
  - Chan-Vese ('99): a LS algorithm depending on a region information model

Comments

- Successful methods
- For model extraction the advantage of having topological changes is not relevant: we need to extract regions with known topology
- Necessity of handling initialization, force definition
  - Several parameters to be controlled
  - Local constraints are sensitive to noise
  - Medical applications often require more constraints to the model (top down approach)

Image information used?

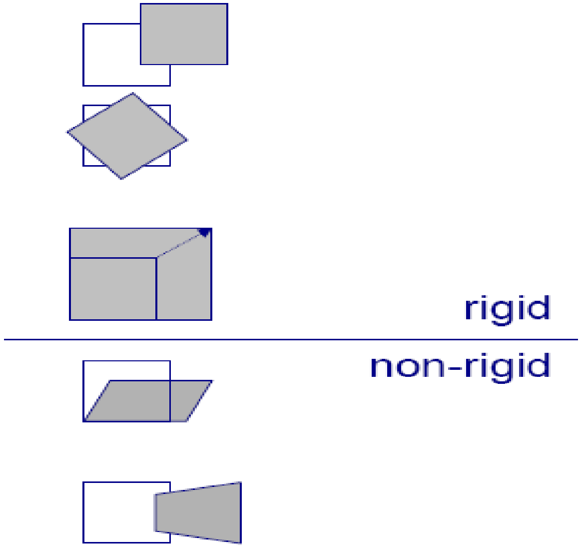
- Simple gradient based attraction (low range)
- Add long-distance gradient effects (distance maps, gradient vector flow)
- Ad hoc local constraints (i.e. attachments)
- Use of full image content (e.g. Chan Vese Approach, not frequent)
- Model based methods (i.e. statistical analysis of gray level profiles near boundaries)
  - Need to have shape constraints

Comments

- Can be interpreted as a "registration" technique
  - Look for a transformation of the boundary surface space into the data space
  - Solved with an optimization procedure minimizing some difference value
  - Usually local optimization methods
- We can limit the allowed transform
  - Use an organ model as initial contour
  - Limit the space transform according to a model
  - Use global optimization

Registration

- A similarity measure
  - Iconic, image based, features
- A parametric transform
  - Translation, Rotation
  - Scaling, Affine, locally affine,
  - Spline, unstructured, example based.
- Solve an optimization problem (find transform parameters maximizing similarity)
  - Deterministic (e.g. gradient based)
  - Stochastic (e.g. Simulate Annealing)



Constrained deformation

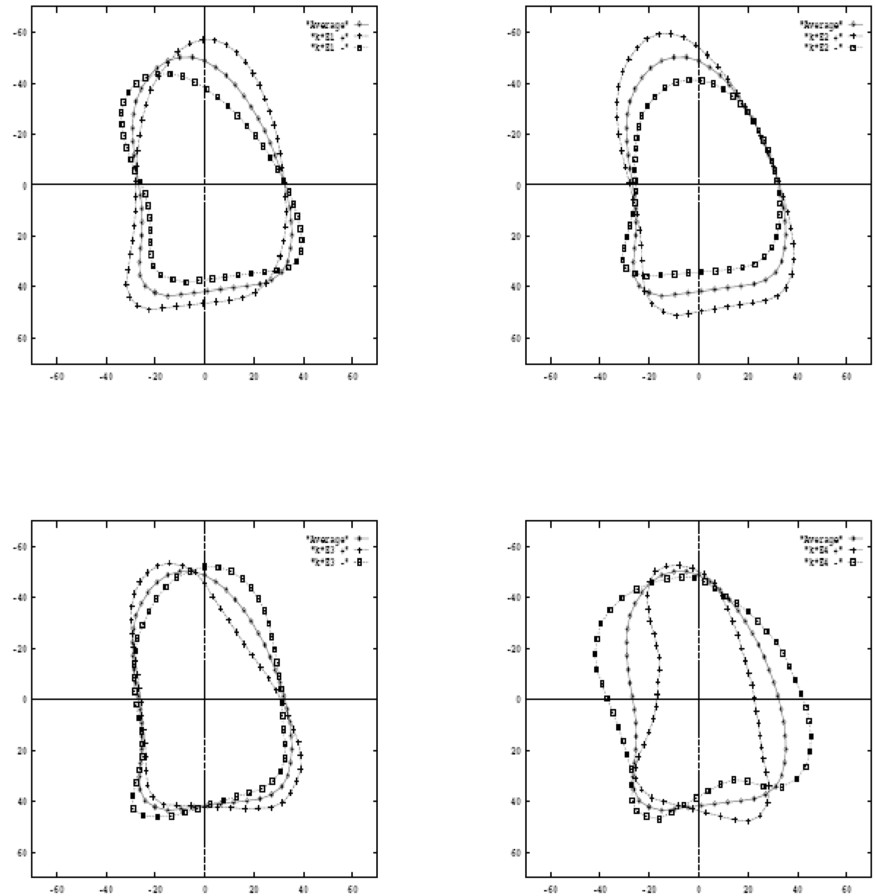
- Fourier models (Staib and Duncan '92)
  - use a truncated series to represent global deformation
- Statistical models: Active Shape, (Cootes & Taylor '94)
  - Use a Point distribution model (Principal component analysis) generated by a training set with corresponding landmark, and constrain allowed deformations to first k eigenvectors
  - Local gray level information can be added to the statistical model (Active Appearance Models '01)

Segmentation method

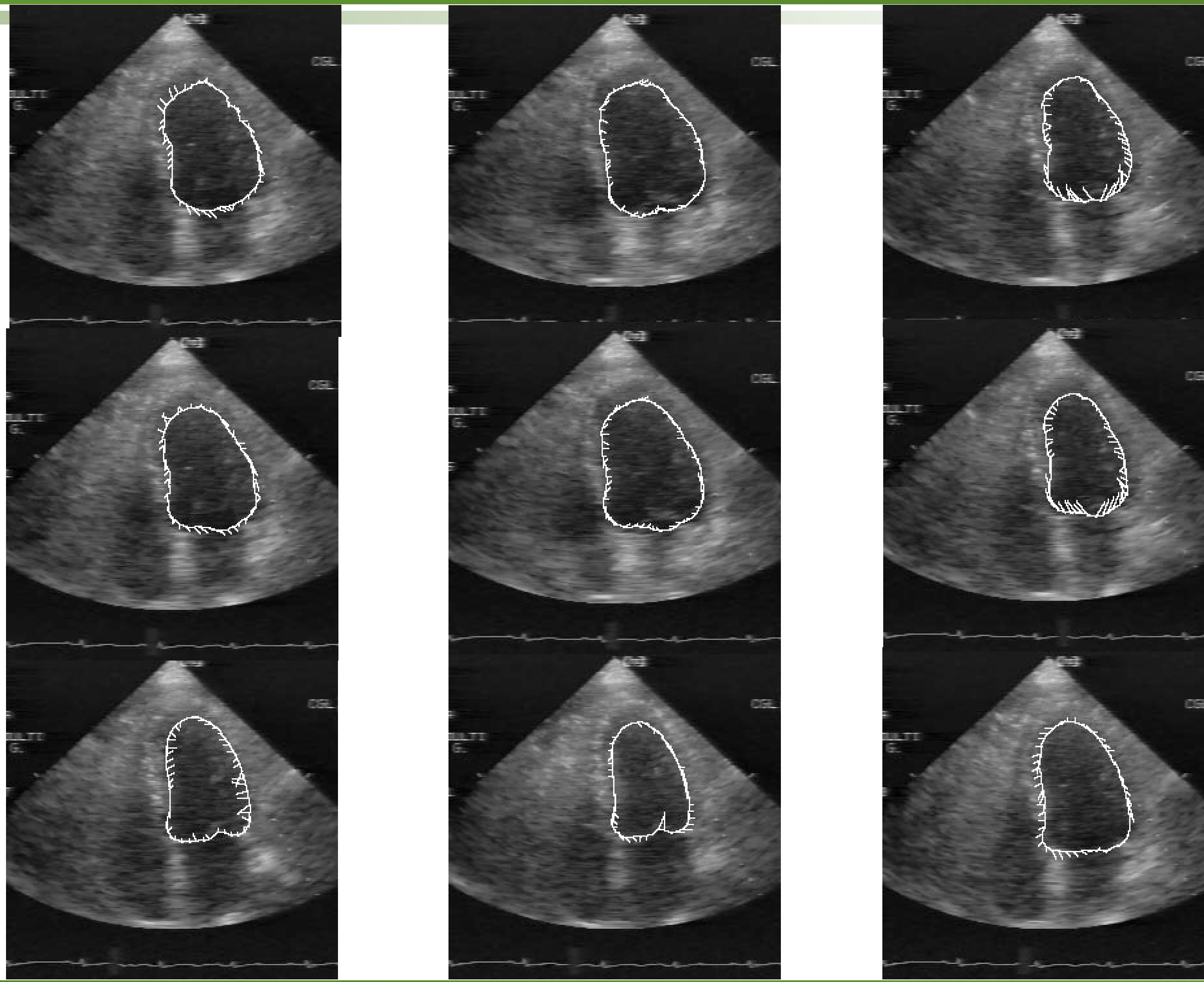
- Compute locally candidate point displacements minimizing image dependent similarity
- Constrain the global displacement to the allowed global components
- Widely applied
- Classical method for Atlas-Based Segmentation
- Contour/surface points have an anatomical meaning

Example

- First 4 eigenvalues of left ventricle deformation (Giachetti and Torre, '98)

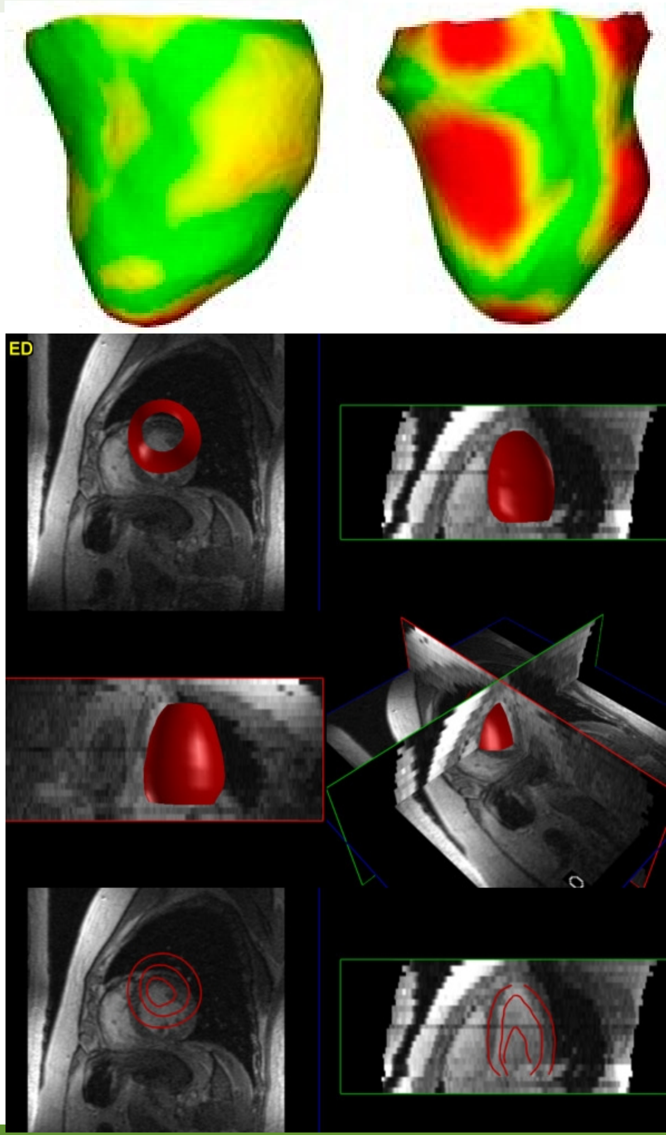


Shape constrained tracking



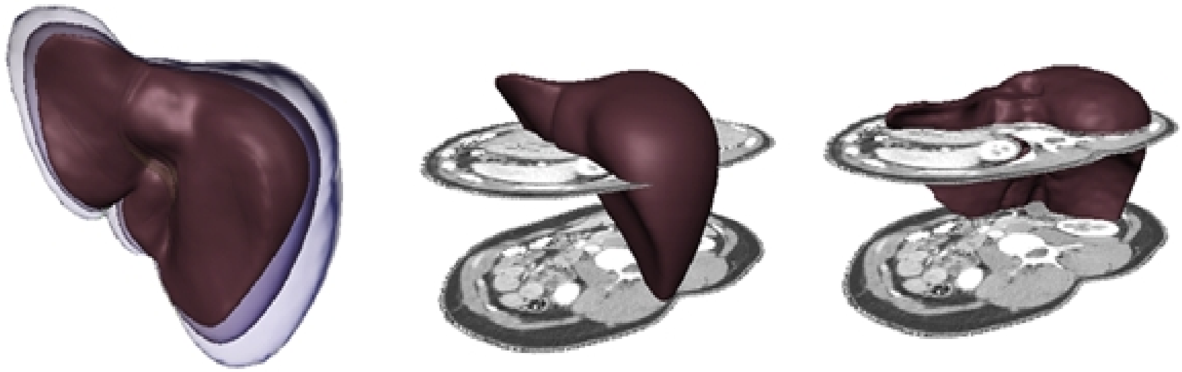
Recent 3D/4D examples

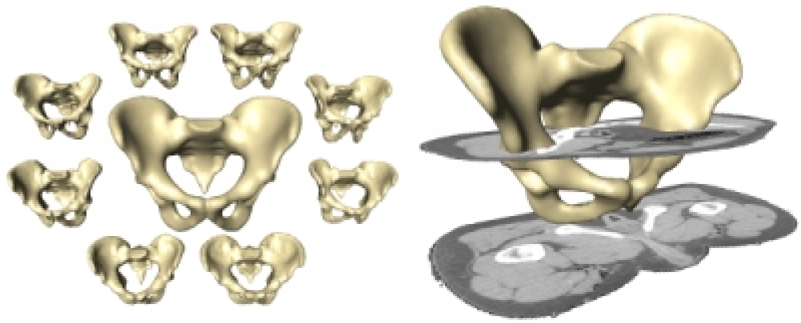
- Heart reconstruction from MRI
  - 3D Active Shape Models, (Van Assen, Frangi et al.'06)
  - Active Appearance Models for Cardiac MRI (Stegmann, Pedersen '05)



Examples

- Atlas based liver/pelvic bone segmentation (ZIB Berlin)





Comments

- Atlas based methods using a AS/AA model are robust and fast, useful for real time tracking, etc.
- Limits
  - Need of point correspondence in statistical models
  - Need of large accurately segmented training sets
  - Global constraints hardly take into account individual peculiarity

Image based/Model based

- Which gives the best result?

Image based/Model based

- Which gives the best result?

Image based/Model based

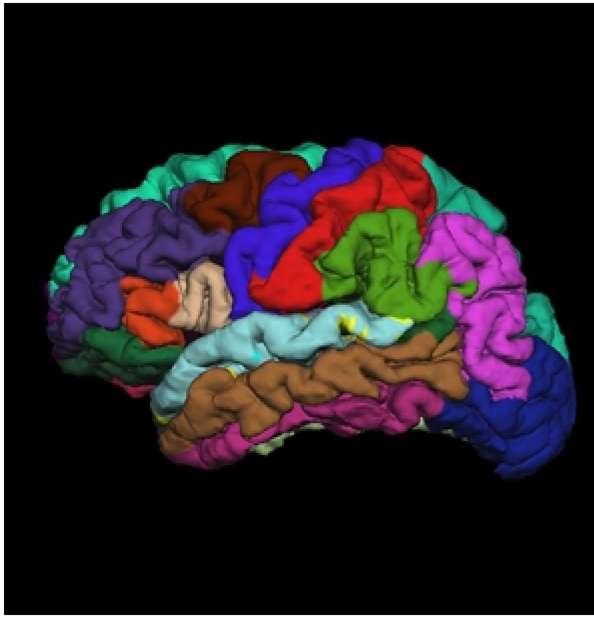
- Which gives the best result?

Image based/Model based

- Which gives the best result?

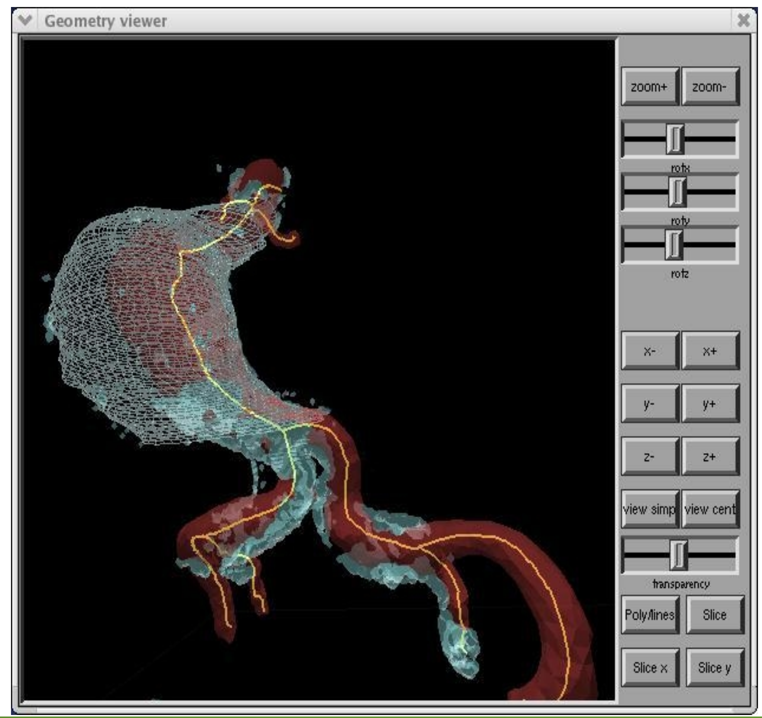
Atlas based segmentation

- Brain parcellation through registration of a manually segmented region (e.g. rigid)
- Can segment data without explicit use of image information
- Registering labeled volume with non labeled volume we obtain a segmentation not using boundary information from images



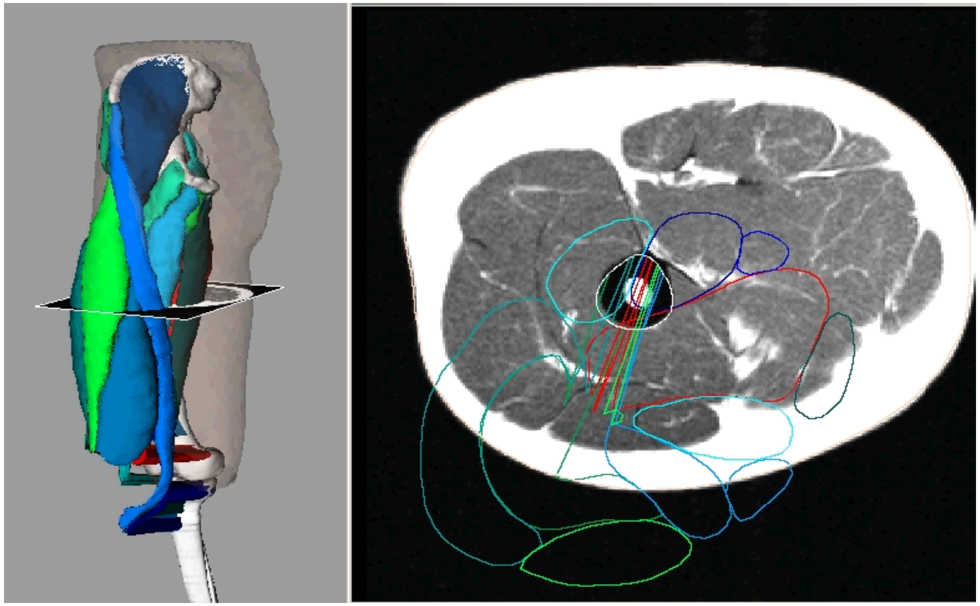
Mixing different constraints

- Creation of complex models using different techniques, constraints and a priori assumptions on relative position of components
- Use of custom image forces (statistical models of gray level profiles/texture)



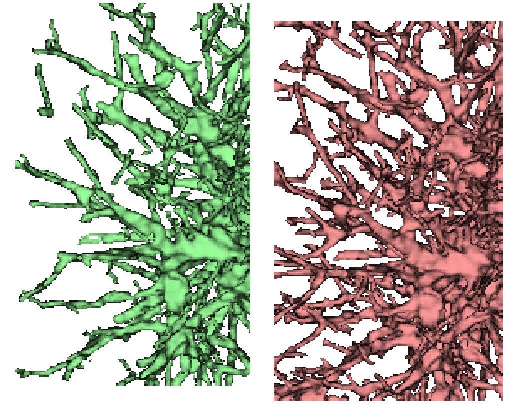
Mixing different constraints

- Muscle segmentation (Gilles et al., 06)
  - Simplex based model
  - topological constraints (attachments)
  - radial forces based on medial axis
  - collision handling

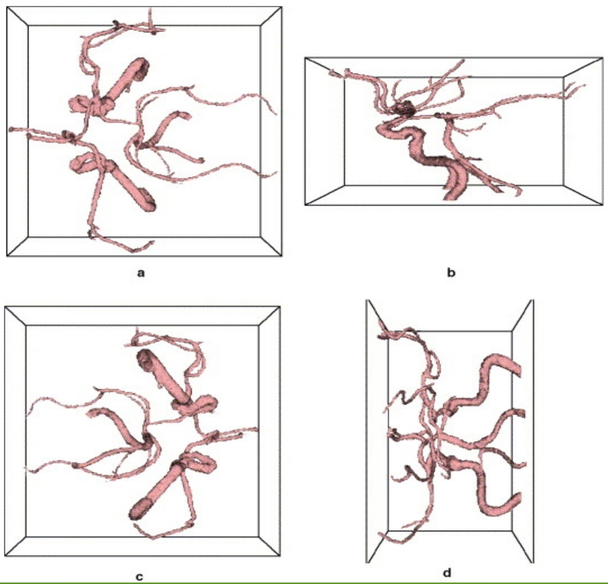


Task related local constraints

- Es. vascular segmentation
- Evolution of a 2D contour in 3D (Lorigo et al . 2001)



- Use of capillary forces (Yan, Kassim '06)



Validation

- Segmentation methods should be validated in order to be used for a particular task
- Necessity of a truth model and a figure of merit
- Different kinds of ground truth data
  - Manually segmented organs
  - Use of computational phantoms
  - Use of physical phantoms
- Different Figure of Merit to evaluate quality
  - Volume based
  - Contour distance based

Validation

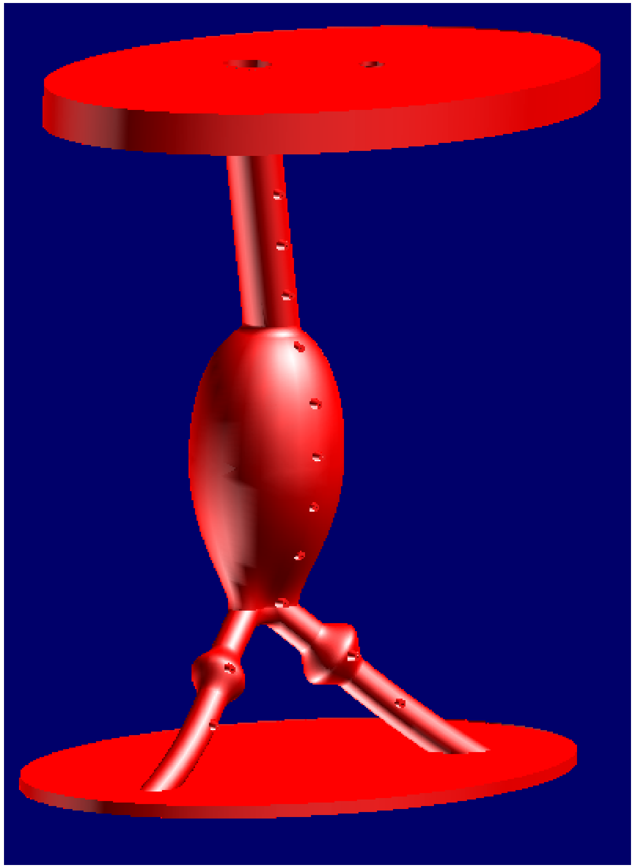
- If user dependent we must also
  - Repeatability, intra-operator variability
- If interactive we must evaluate
  - Time requirements

Figure of merit

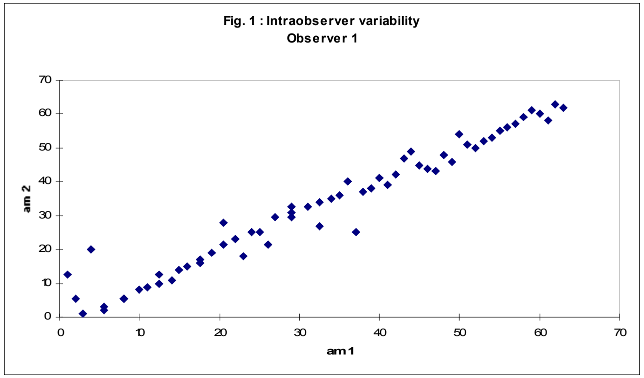
- Depends on the application requirements
  - Example: symmetrized volume $(VS \cap VT) / ((VS + VT)/2)$
  - May underestimate local problems (i.e. large distance from correct boundaries In selected locations)
  - Is it a good measure?
  - Yes, if the application estimates volumes for clinical applications, e.g. ejection fraction
  - Not necessarily if we need to capture surface anomalies

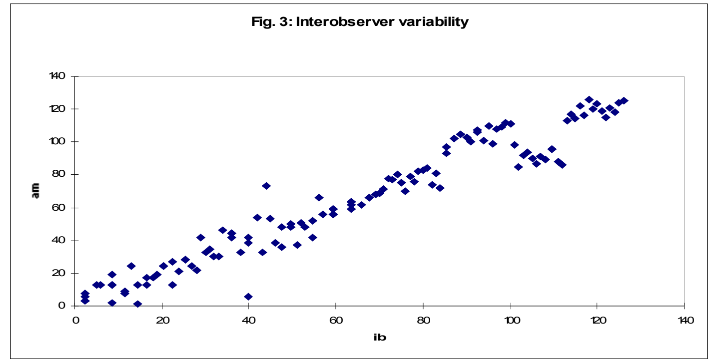
Example: aortic reconstruction

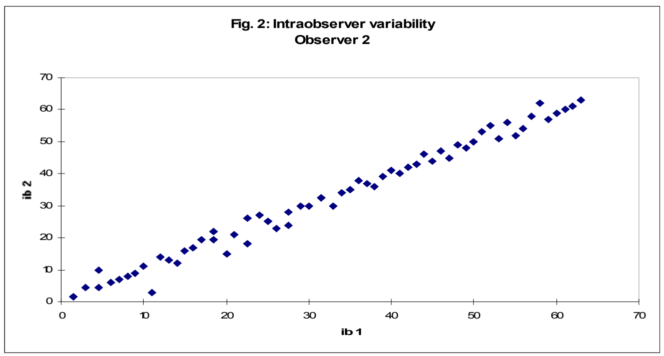
- AQUATICS Project
- Measurements on phantom
- 8 models, scanned at different protocols (1-5 mm)
- Models measured independently by three different (remote) operators,
- 8 models reconstructed independently by two operators
- Patient data
- 5 models reconstructed twice for control
- 40 models created and measured independently in the three locations

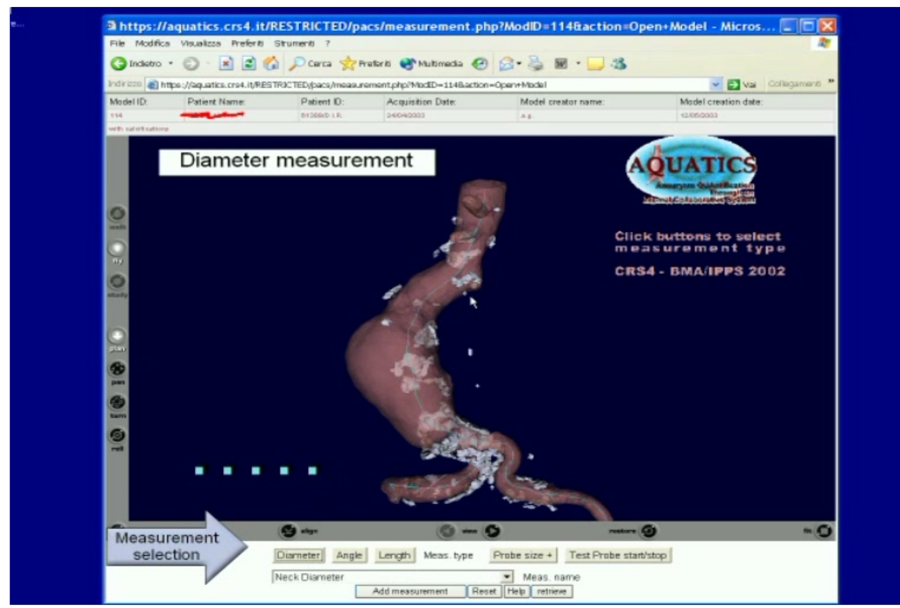


Rank tests









Good results

- low intraobserver variability ($p<0.0001$)
- significant correlation

between observers ($p<0.0001$)

Example

- Reconstruction validated through clinical parameters evaluation, comparing with phantom real measures or other methods

Measurement	GE AVA	AQUATICS
Proximal neck diam	21.6	20.4
Left common iliac diam	11.5	12.6
Right common iliac diam	11.8	11.6
Proximal neck length	48	48.1
Renal-aortic bif. length	122	110
Renal-left iliac length	160	153
Renal-right iliac length	168.4	161
Aortic bif-left iliac length	49.3	45.7
Aortic bif-right iliac length	66.8	56.6
Proximal neck angle	151	167
Sac – left iliac angle	140.6	151
Sac – right iliac angle	172.4	167

Comments

- Validation method and figure of merit depend on the task
- For clinical applications a clinical validation is required

Conclusions

- Different approaches to medical image segmentation (and many equivalent formulations)
- Local, image based methods depend largely on the choice of ad hoc image forces/potentials
- A key factor to obtain good results is to decide how much of image based/a priori information to use
  - Methods based on shape constraints and local appearance modelling are robust and provide good models, not always suitable for clinical applications