GREYC Image - UMR 6072

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Statistical Shape Model-based Segmentation of brain MRI Images

Jonathan Bailleul, Su Ruan, Jean-Marc Constans

1. Context

2. Need for shape priors.

3. Introduction to the Point Distribution shape Model (PDM)

4. Automatic construction of PDMs in 3D MRI

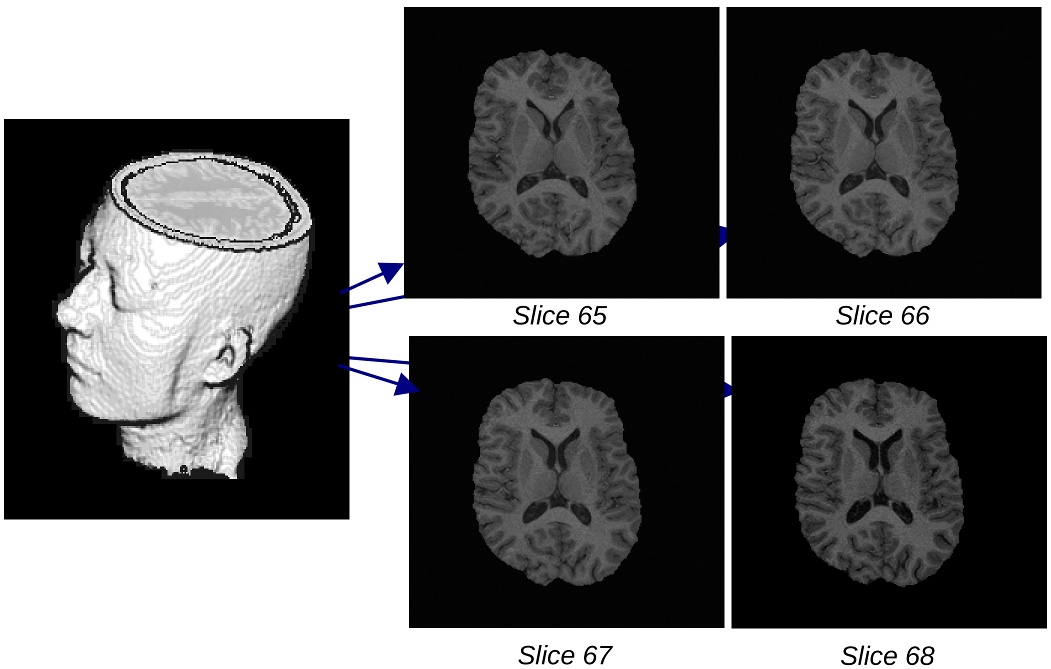
5. Improved Active Shape Model

Automatic delineation of deep nuclei in 3D brain MRI

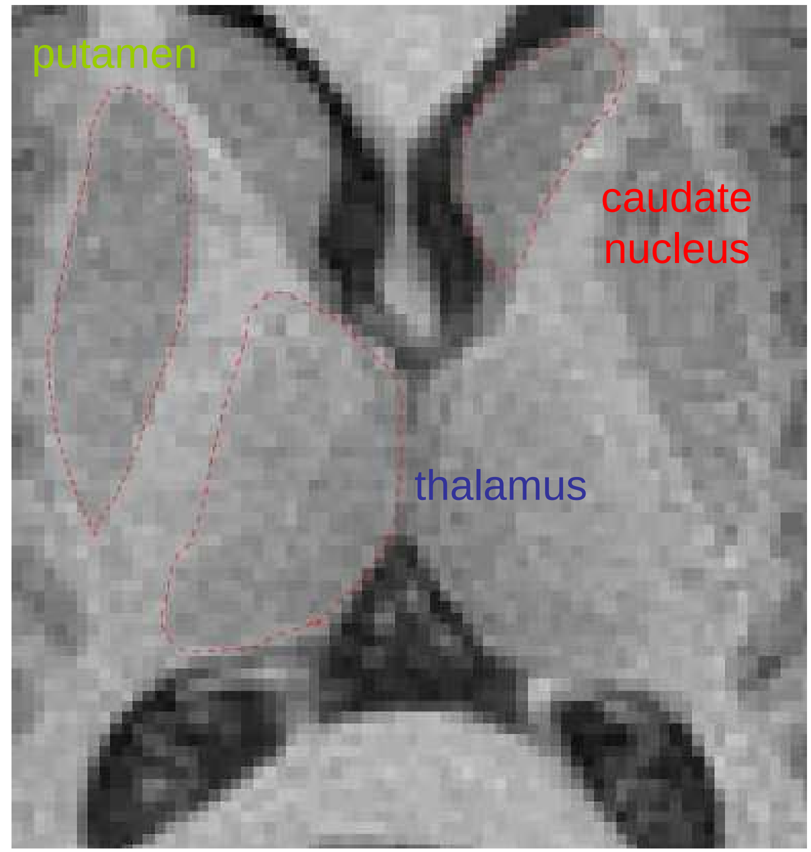
Target

Input data: Brain MRI

- T1-ponderated « anatomical » MRI
- Dimension: 256x256x124 voxels
- Spatial resolution: 1mm (isotropic)

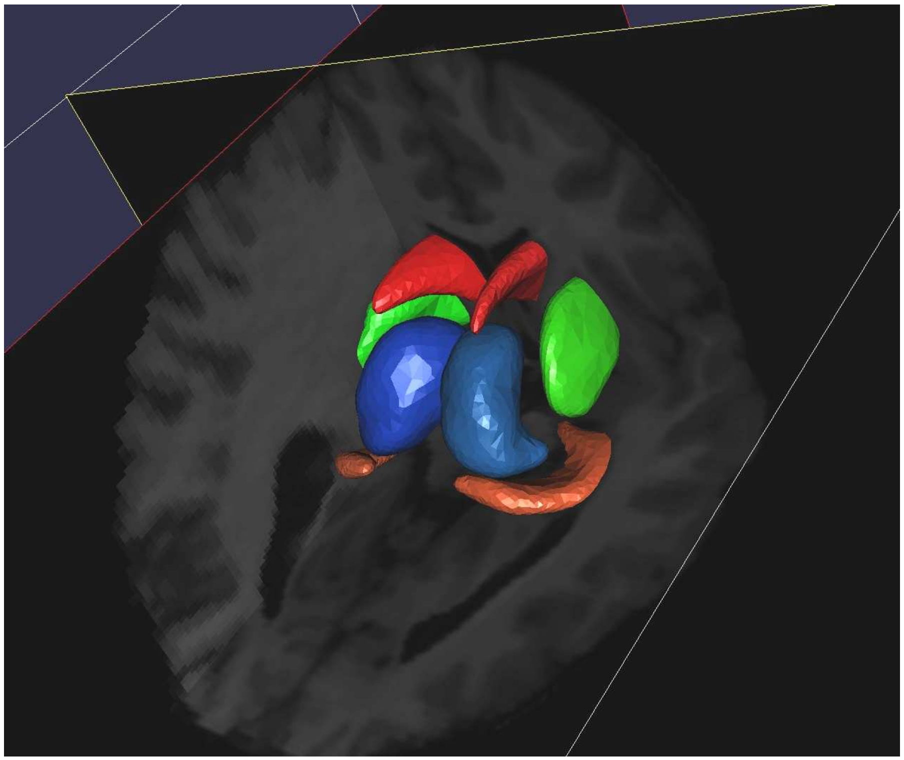


Delineation of deep brain anatomical structures

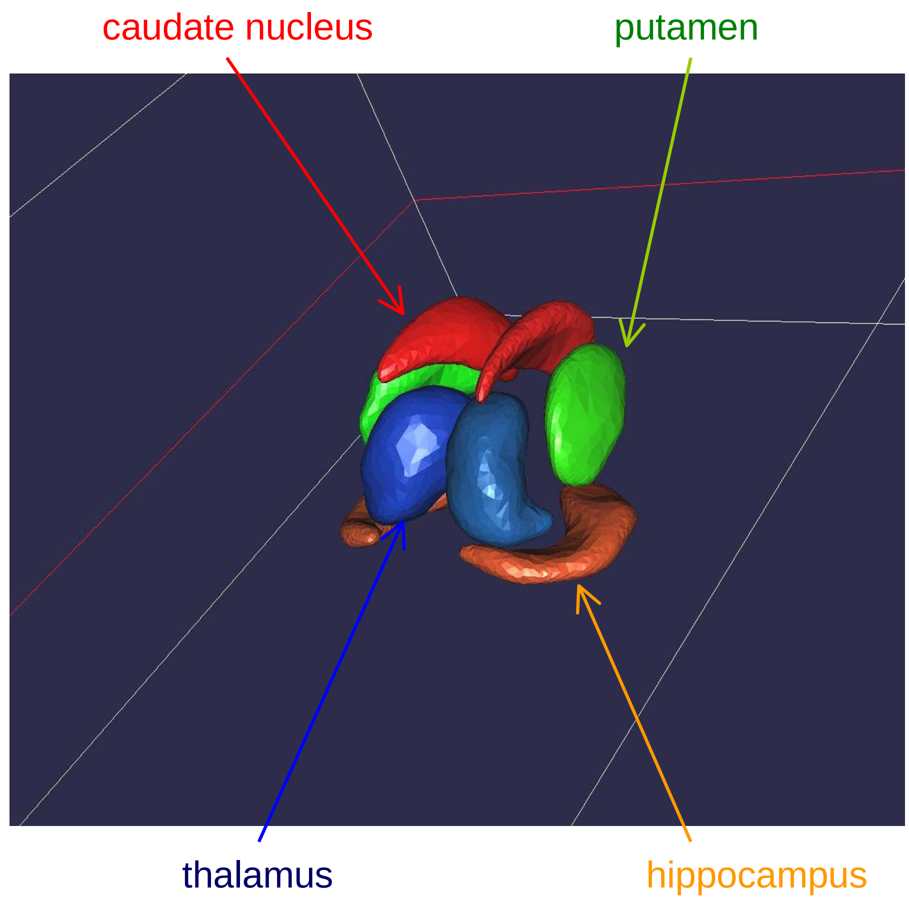


Automatic delineation of deep nuclei in 3D brain MRI

Target



(volume: Atlas Harvard SPL)



A tool for neuroanatomic studies

Purpose

Statistical studies on MRI databases:

- **Functionnal brain mapping:**

  Anatomic localization (IRM) of functionnal activation signals (IRMf) occuring when the patient performs a given cognitive task (e.g calculus)

- **Characterizing neurologic pathologies :**

  • Parkinson disease alters thalami/hippocampi volumes.

  • Schizophrenia alters the shape of hippocampi.

- **Data mining:**

  Blind research of correlations between patient features (e.g gender, handedness) and nuclei features (e.g shape, volume)

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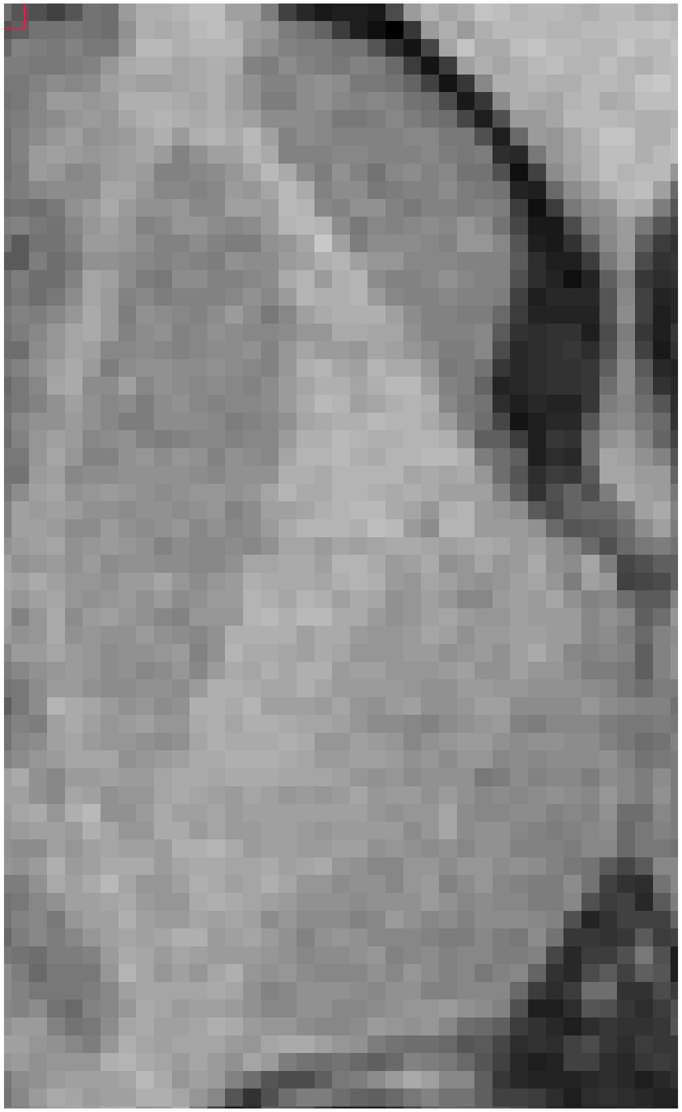
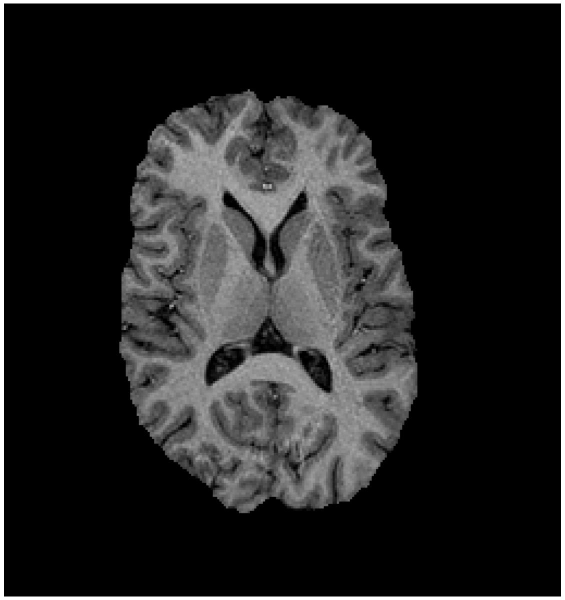
Unreliable boundary information

Practical problem

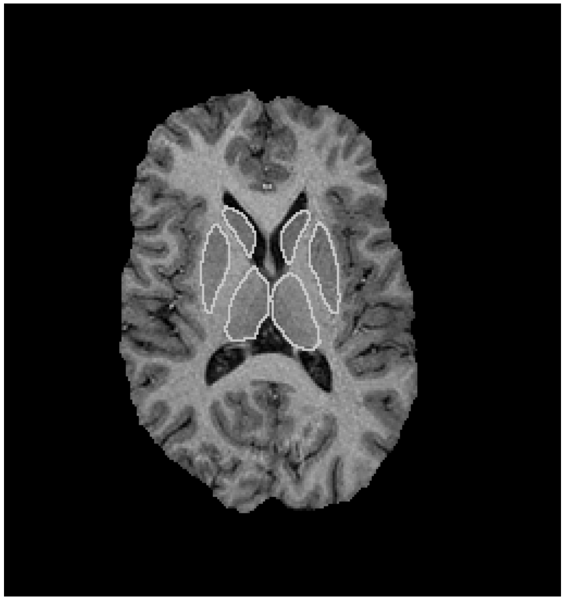


zoom on region of interest

MRI slice sample



Expected delineation



a priori information
is required to achieve delineation

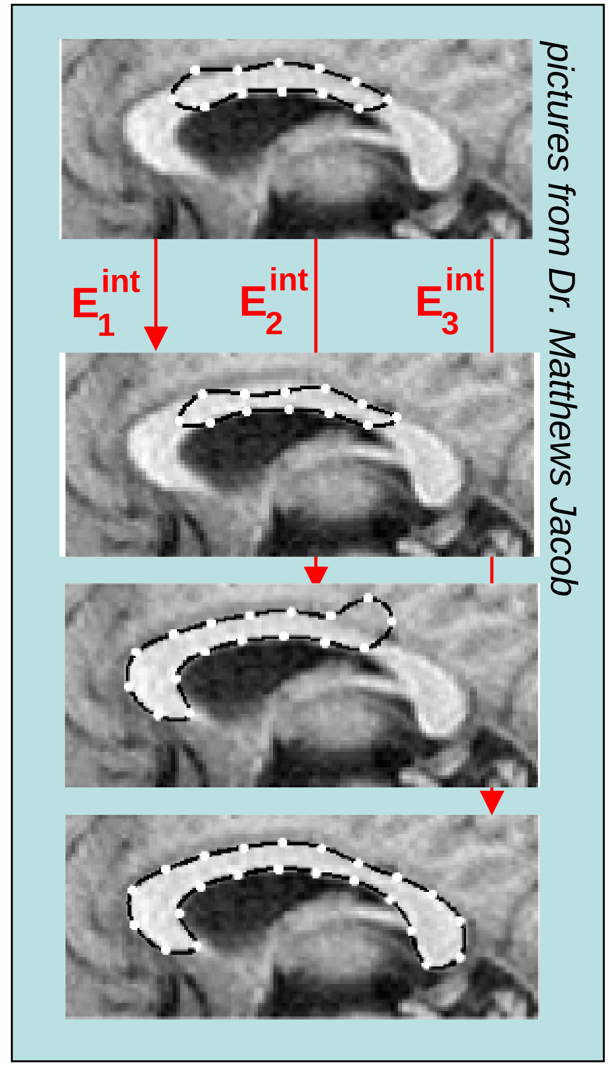
Delineation is achieved in minimizing the sum of two energies:

a) ***external energy***, **driving points towards the estimated boundary.**

b) ***internal energy***, **minimizing:**

- **contour lenght** ***(elasticity)***
- **contour curvature** ***(rigidity)***

➡ ***A priori hypotheses on internal energy can be too loose***



Mathews Jacob, Thierry Blu, Michael Unser: ***«Efficient Energies and Algorithms for Parametric Snakes»***, IEEE Transactions on Image Processing, vol. 13(9), Nov 2004

Statistically deformable contour and surfaces

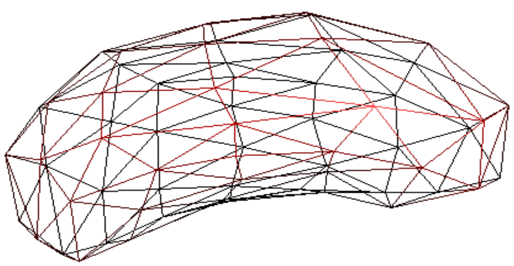
Using a priori information

A case study on the 3D discrete ‘smart snake’ (PDM)

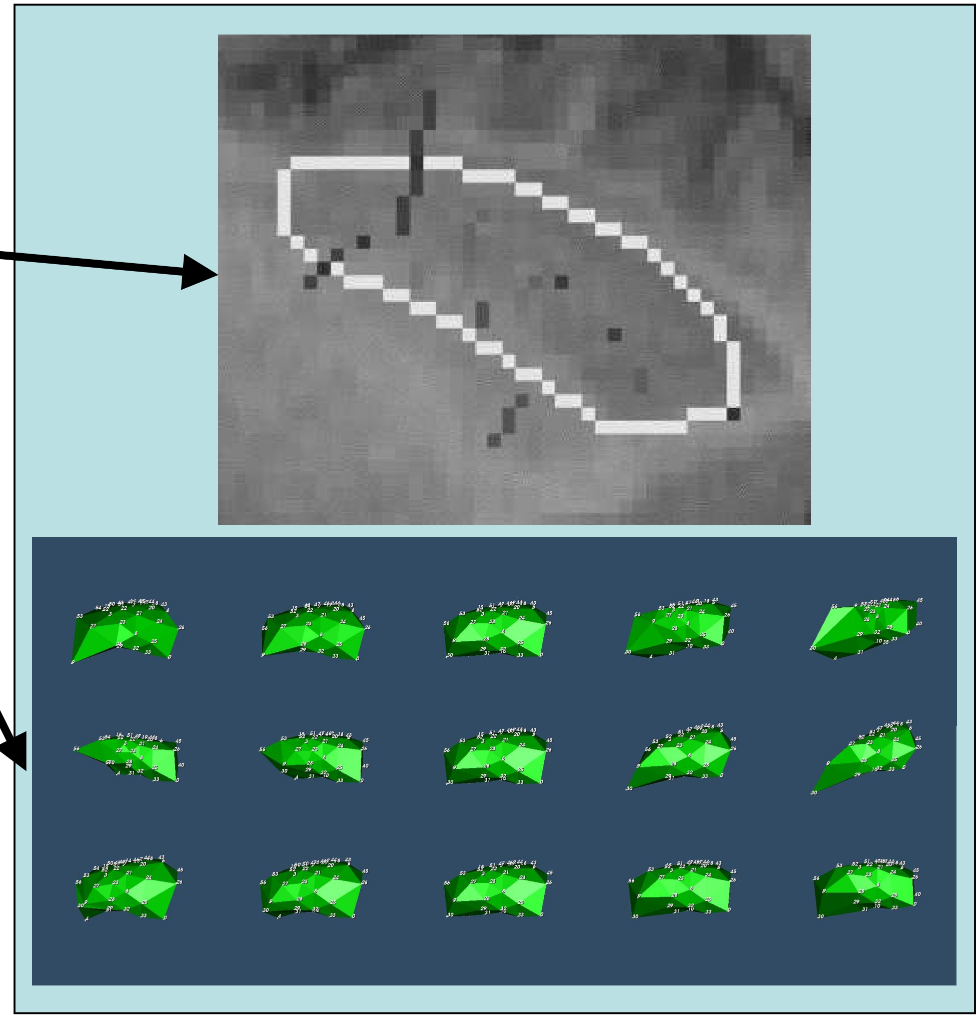
Delineation is achieved when iterative deformation of the prototype reaches idempotence:

a) *the Intensity Model proposes a move for each point in surface normal direction*.

b) *the Statistical **Shape** Model (PDM),* amends the previous moves so as to ***enforce shape constraints*** on the prototype.



Shape prototype



Cootes, Taylor, Cooper, Graham: ***« Active Shape Models – Their Training and Applications »***, Computer Vision and Image Understanding, 61(1), pp 38-59, 1995.

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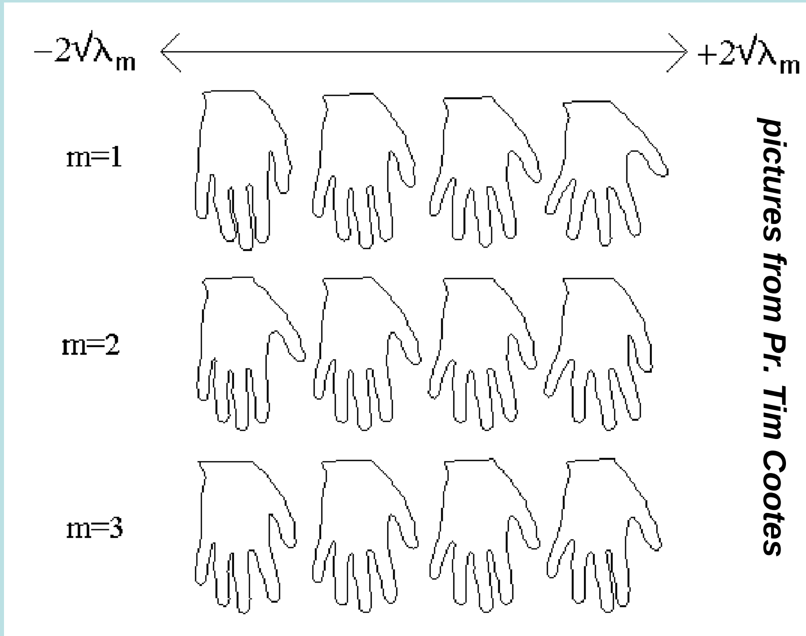
Point Distribution Model (PDM)

Input data: **a training set of outlines of the shape to learn**

output data:

A shape model*:*

- ➢ generating likely shape instances
- ➢ determining wether an arbitrary instance matches learned shape

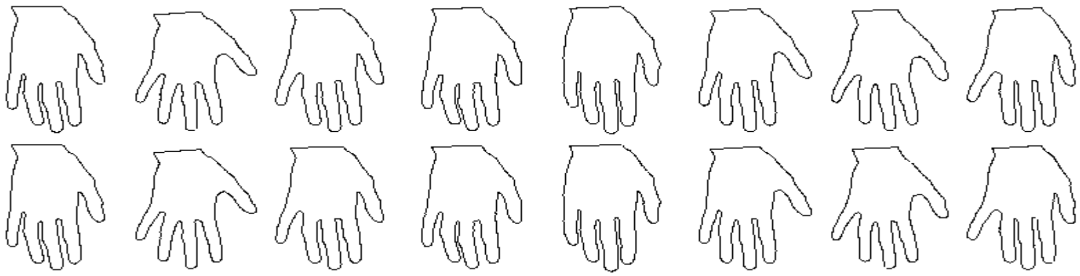


pictures from Pr. Tim Cootes

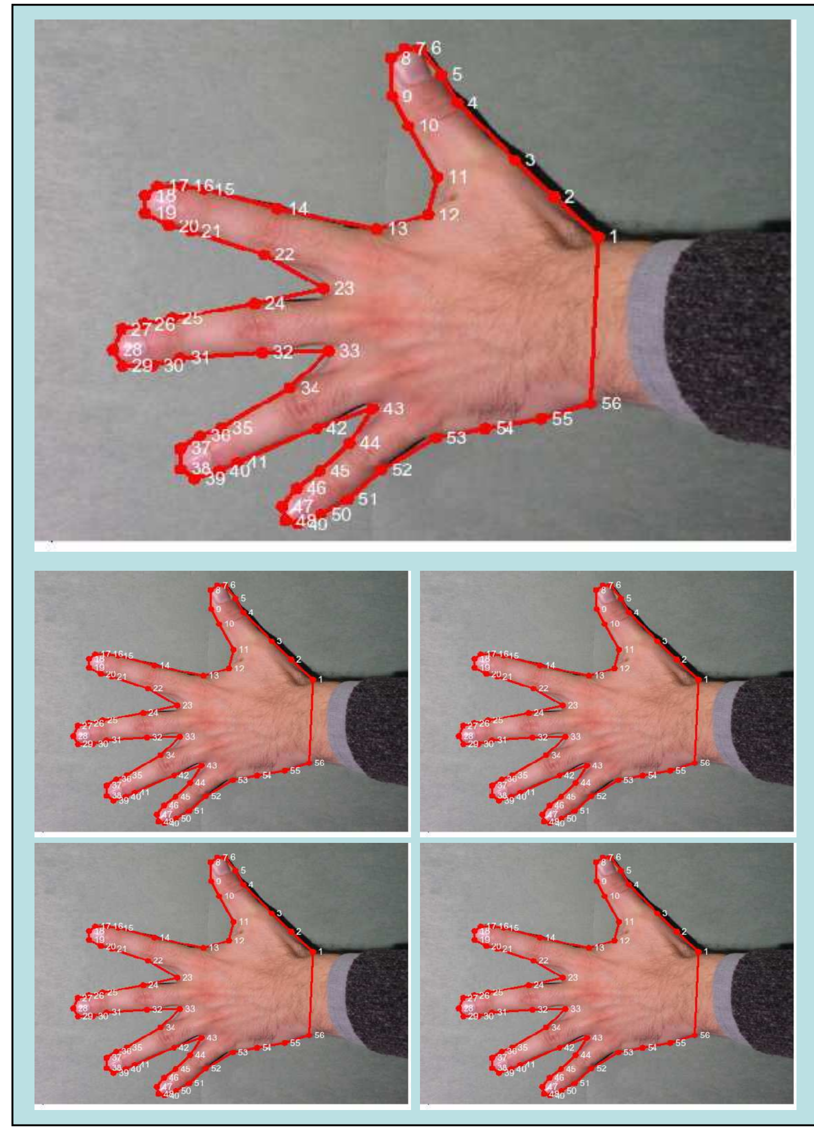
→ **Explicit a priori shape information**

Cootes, Taylor, Cooper, Graham: « ***Active Shape Models – Their Training and Applications*** », Computer Vision and Image Understanding, 61(1), pp 38-59, 1995.

Point Distribution Model (PDM)



- We must first collect various outlines of the shape to learn
- Each shape instance must be annotated by corresponding landmark points

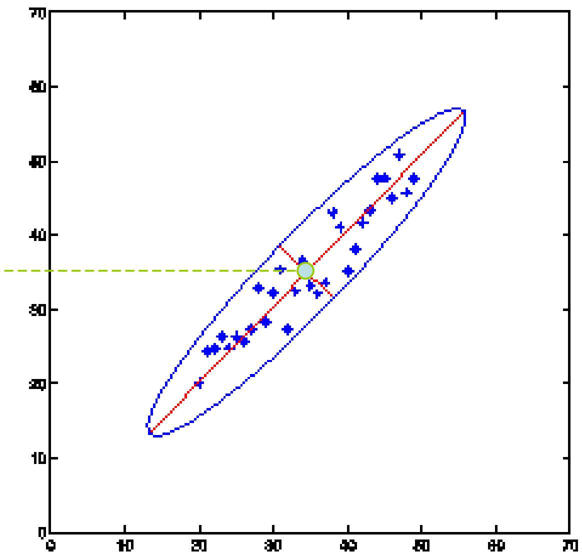


« A landmark is a point of correspondence in each object that matches between and within populations » [1]

[1] Dryden, Mardia: ***« Statistical Shape Analysis »***, Wiley, 1999

Point Distribution Model (PDM)

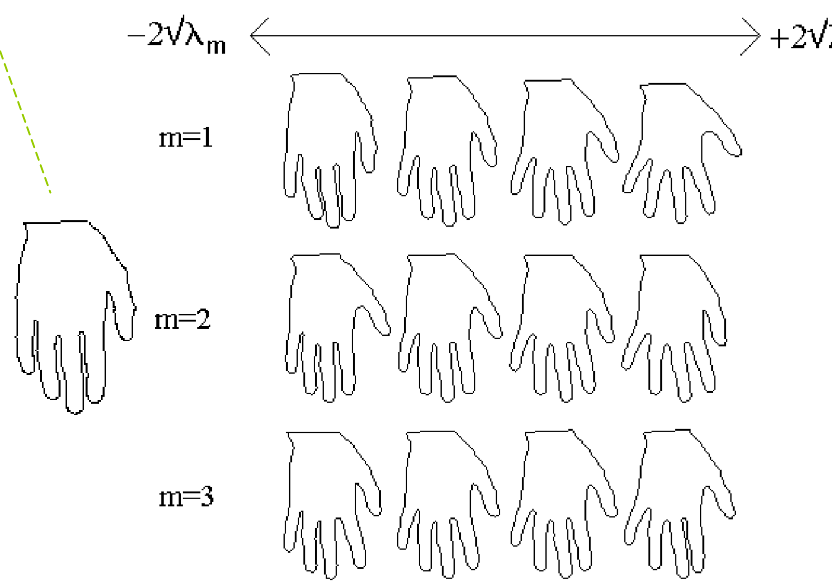
- Each instance annotated by n landmarks
- landmarking m shape instances in a 2D space produces m dots in a $2n$-dimensional space.
- A mean shape X_m is computed by averaging.
- PCA can extract eigenvectors p_k and associated eigenvalues v_k.



We can define an **« *Allowable Shape Domain* »** (ASD) as: $$x = X_m + Pb$$

- **P**: $(p_1, p_2, \ldots, p_t)$, matrix of most significant eigenvectors
- **b**: $(b_1, b_2, \ldots, b_t)^T$, a set of bounded shape coefficients

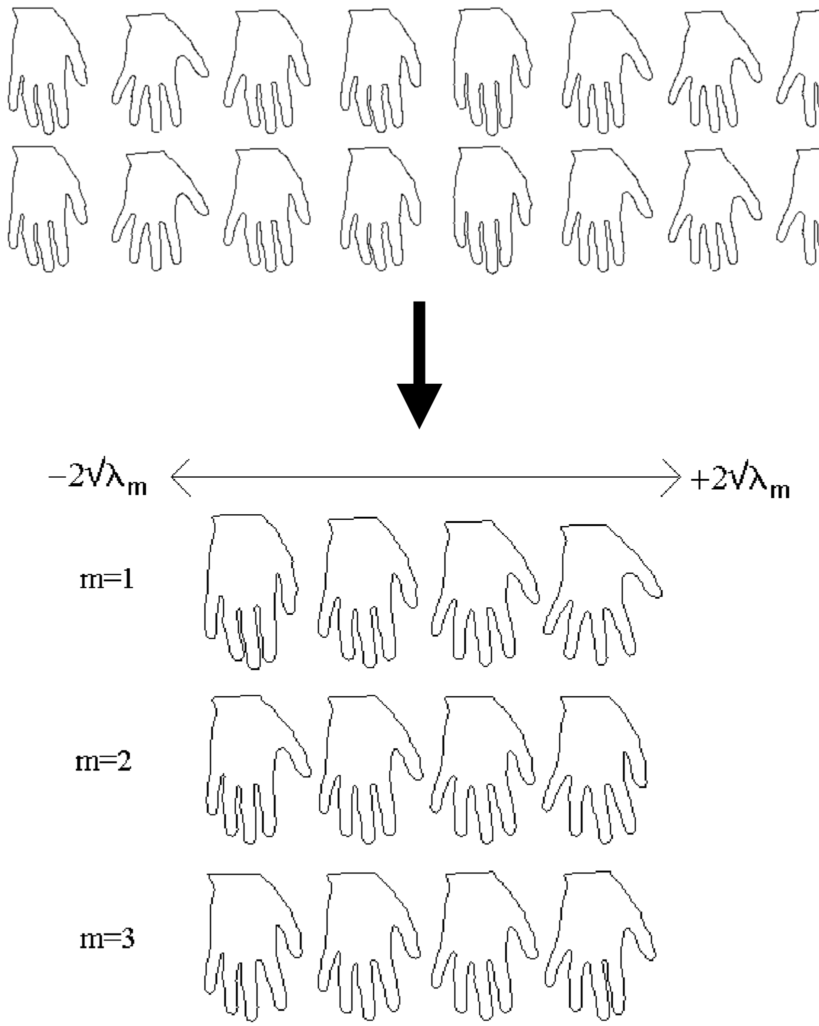
$$|b_k| <= 3*\mathrm{sqrt}(v_k)$$

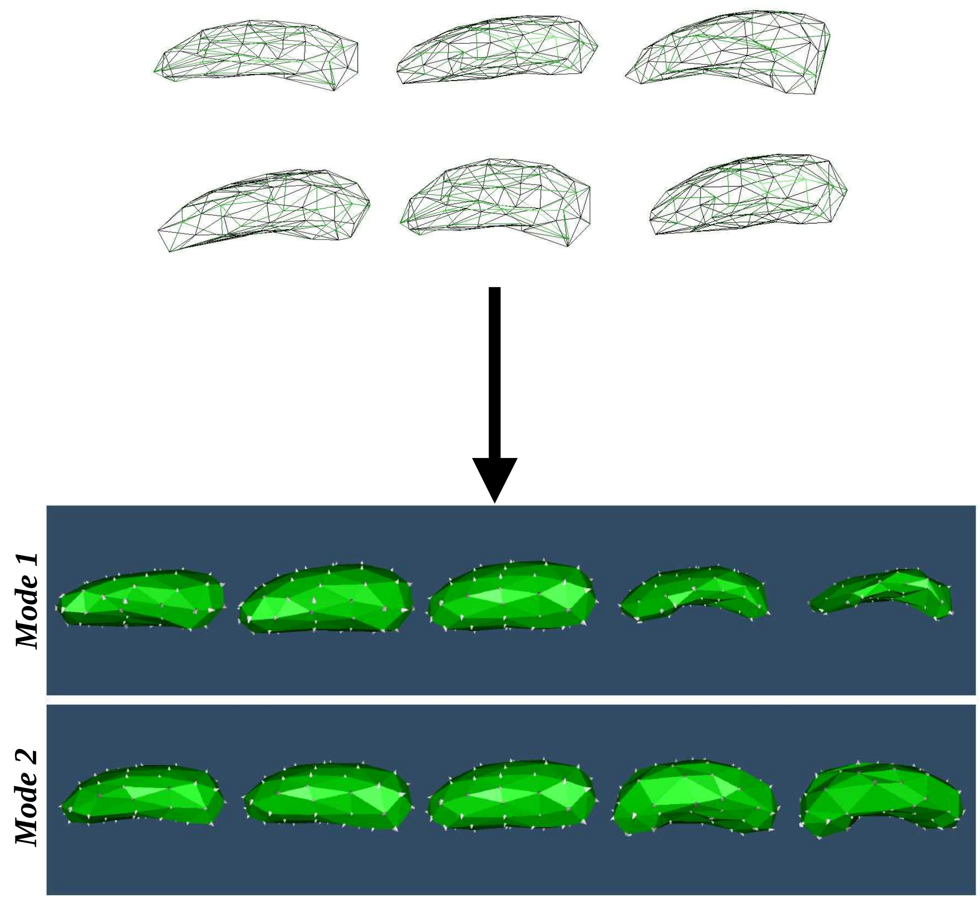


Cootes, Taylor, Cooper, Graham: **« *Active Shape Models – Their Training and Applications* »**, Computer Vision and Image Understanding, 61(1), pp 38-59, 1995.

Point Distribution Model (PDM)

No dimensional limits





- **Frangi, Rueckert et al.**
- **Gerig et al.**
- **Kelemen, Szekely et al.**
- **Pitiot, Thompson et al.**

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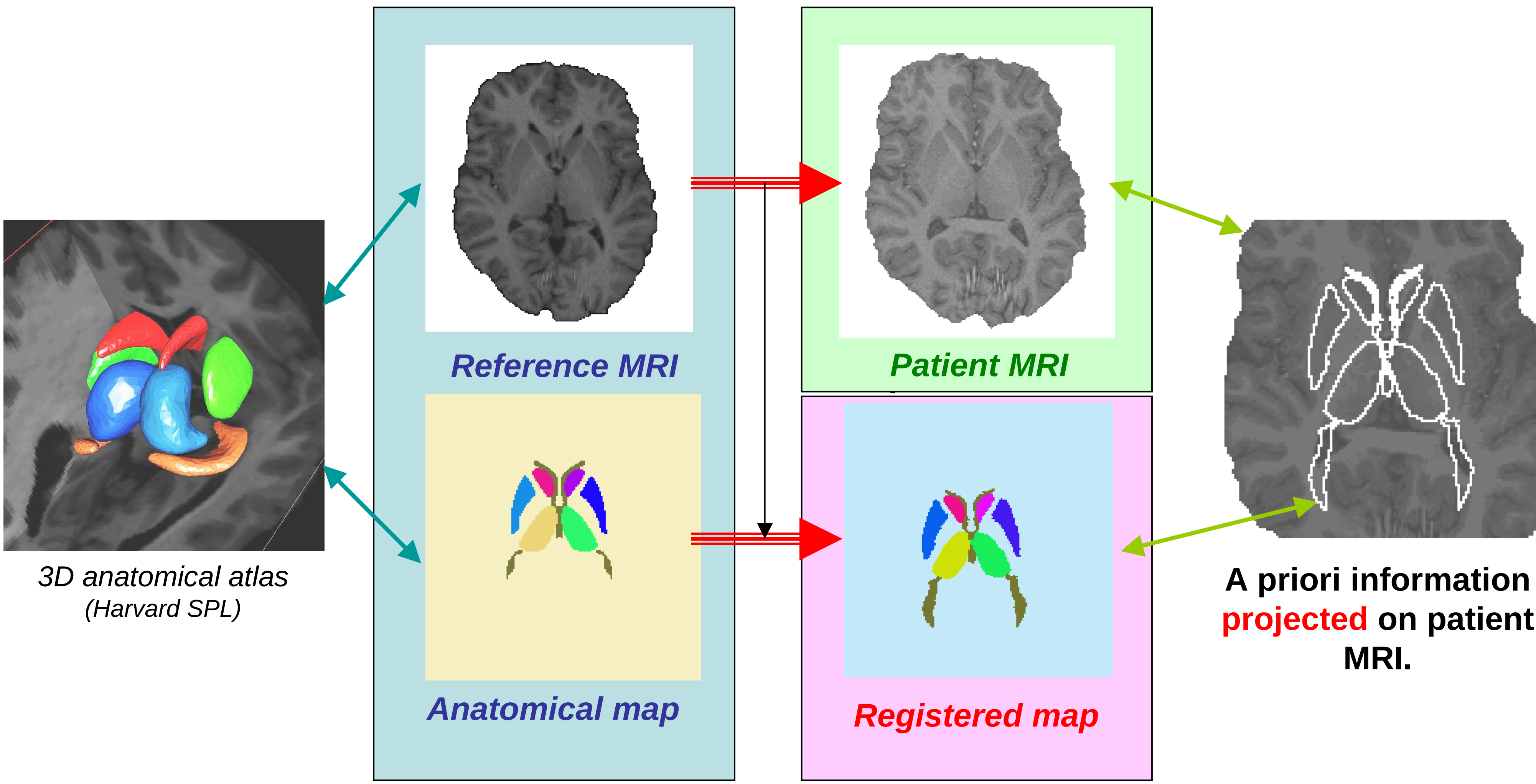
Automatic 3D PDM Building:

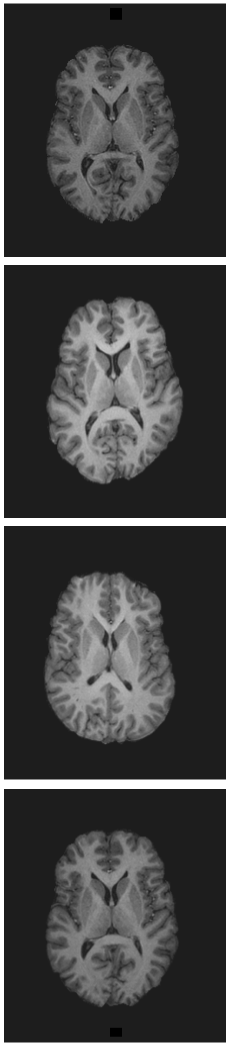
Atlas Registration Overview

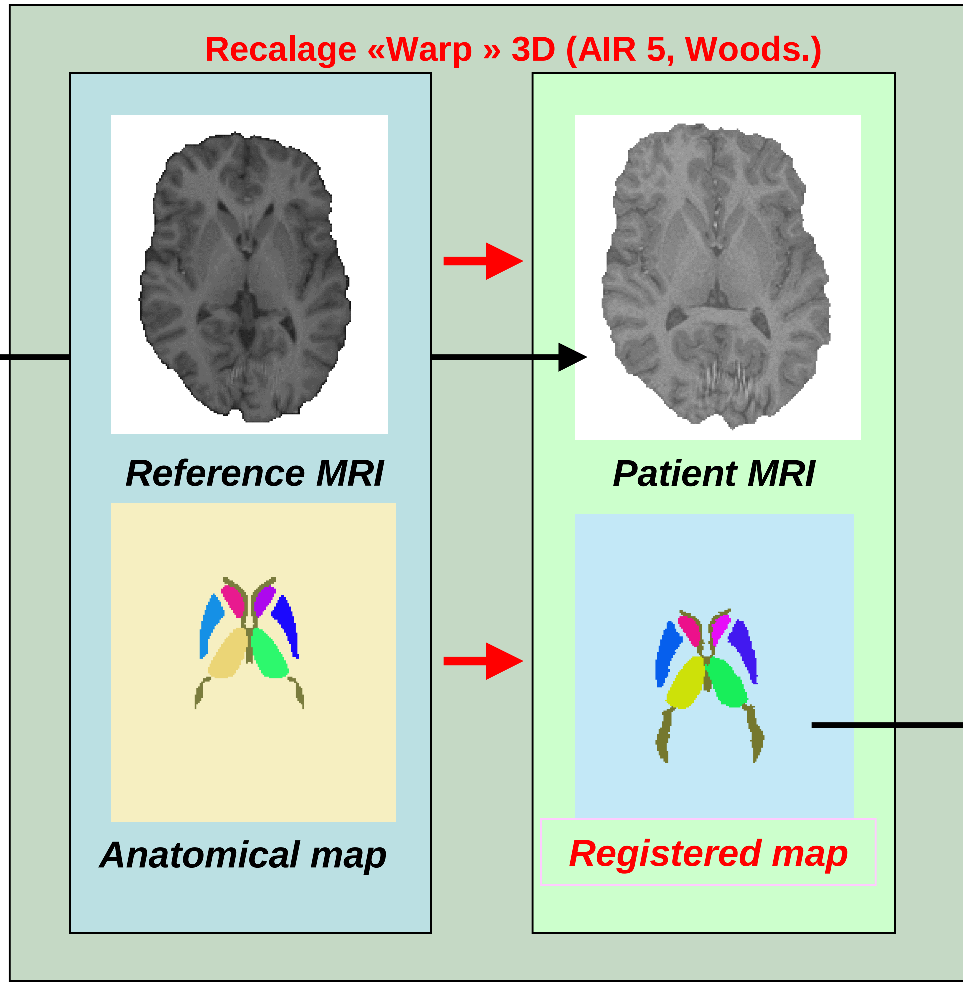
3D Registration *(« Warp »,* AIR 5, Woods.)

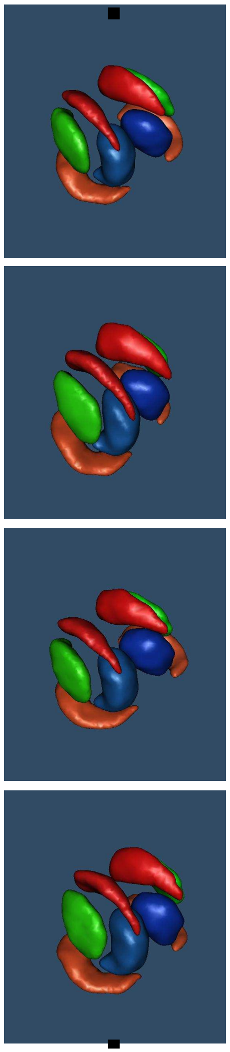


Automatic 3D PDM Building:

Training set building using atlas registration

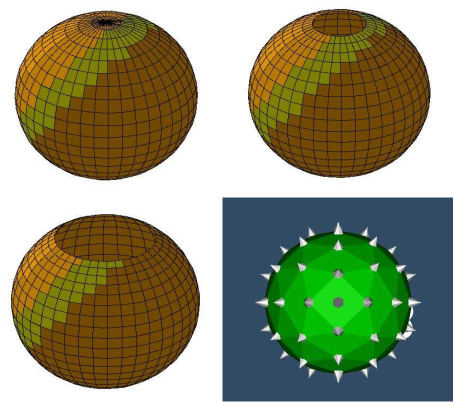






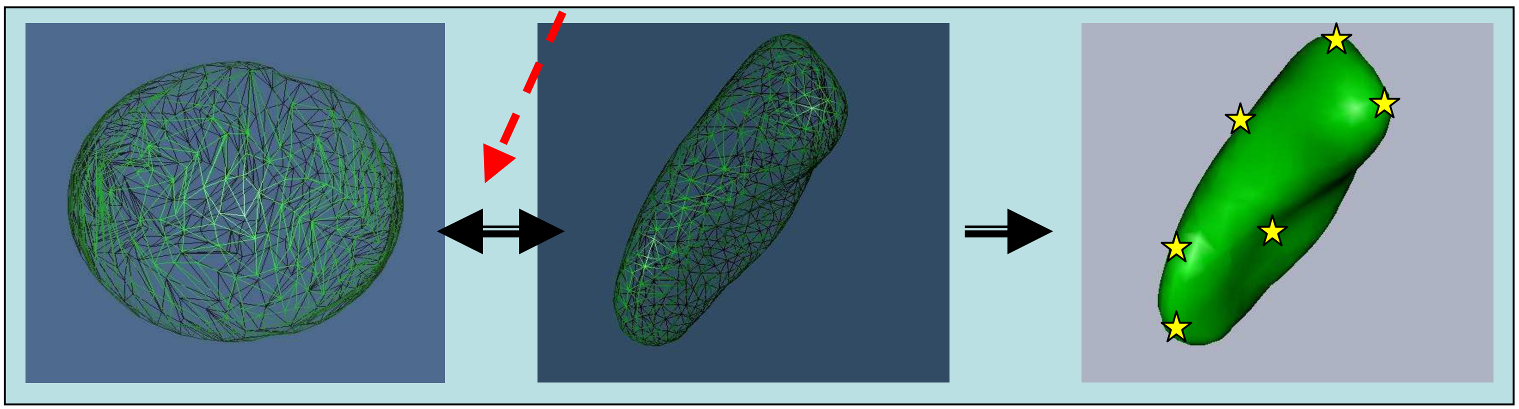
Automatic 3D PDM Building:

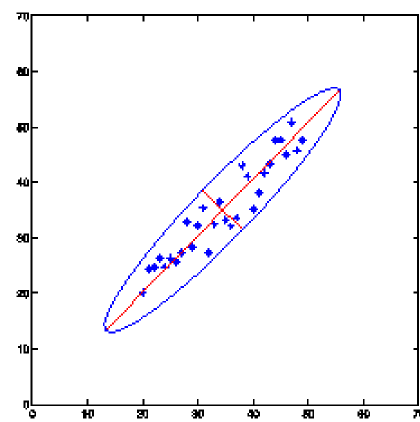
Automatic landmarking



$$f(\theta) = \frac{1}{1+A}\left(\theta + \arccos\left(\frac{(1+\alpha^2)\cos\theta - 2\alpha}{1+\alpha^2-2\alpha\cos\theta}\right)\right)$$

- Cauchy kernels allow compact parameterization of n landmarks on a unit sphere
- Correspondences between shape instances and triangulated spheres are computed once by conformal projection
- Simplex optimizes parameterization in quantifying compactness and accuracy of the resulting PDM





Davies, Twining, Cootes, Waterton, Taylor: ***« A Minimum Description Length Approach to Statistical Shape Modeling »***, IEEE Trans. Med. Imaging, vol. 21(5), May 20

Allan Reinhold Kildeby, Rasmus Larsen: ***« Building optimal 3D shape models »***, Masters Thesis, IMM, Technical University of Denmark, 2002

Variation modes samples

Putamen (left instance):

Mode	1	2	3	4	5	6	7	8	9	10
% variance	22.87	17.07	11.08	9.31	7.24	6.14	3.77	2.97	2.74	2.41

Automatic 3D PDM Building:

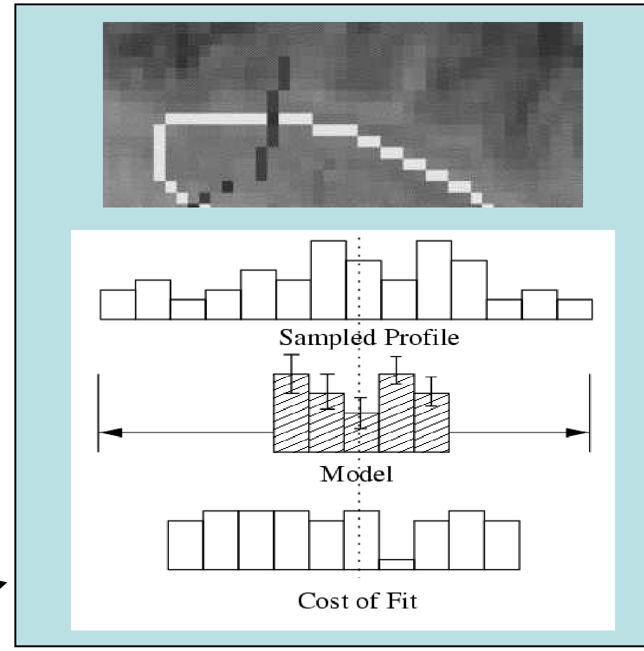
Summary of contributions

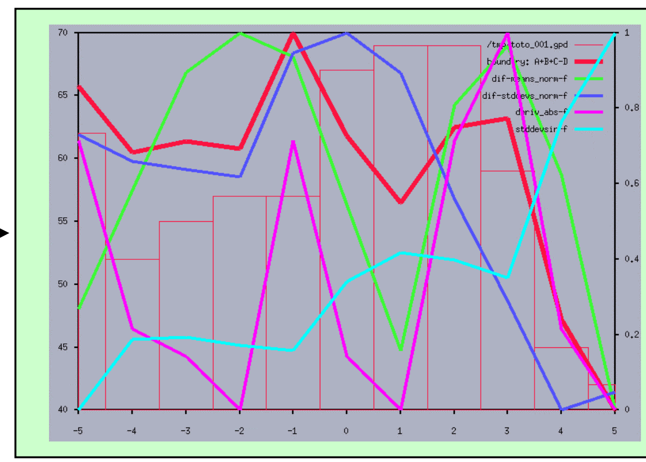
Contribution:

- no need for (very very) tedious expert delineation or landmarking [2]

Drawbacks:

- No exact correspondence between automatic delineations and MRIs
- The standard statistical Intensity Model is then no more applicable [1]
- A new Intensity Model had been specifically designed [3]





[1] Cootes, Hill, Taylor, Haslam: ***«Use of Active Shape Model for locating structures in medical images»***, Image and Vision Computing, vol. 12(6), June 1994.

[2] Bailleul, Ruan, Bloyet, Romaniuk: ***«Segmentation of Anatomical Structures in 3D Brain MRI using automatically built Statistical Shape Models»***, IEEE ICIP, Oct 2004, Singapore

[3] Bailleul, Ruan, Bloyet: ***«Automatic Atlas-Based building of Point Distribution Model for Segmentation of Anatomical Structures in 3D Brain MRI»***, IEEE ISSPA, July 2003, Paris

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Active Shape Model

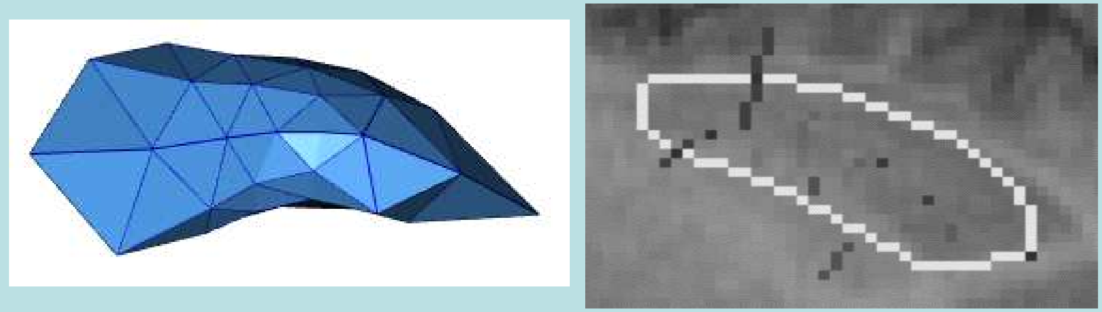
A detailed overview on th
standard framework

a) *The landmarked shape prototype is posed into MRI as close as possible to actual contours*

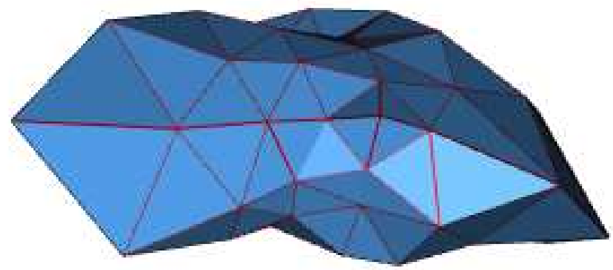
b) *the Intensity Model proposes a move for each point in surface normal direction*.

c) *the Statistical **Shape** Model (PDM) finds the closest shape instance from the Allowable Shape Domain (ASD)*

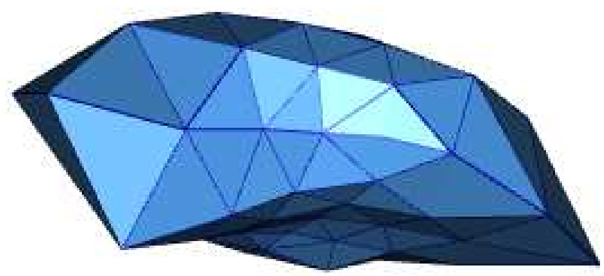
d) *Repeat b+c until idempotence*



shape prototype posed on MRI



prototype adapted towards closest boundary



shape prototype posed on MRI

Cootes, Hill, Taylor, Haslam: ***«Use of Active Shape Model for locating structures in medical images»***, Image and Vision Computing, vol. 12(6), June 1994.

Active Shape Model

Main limitations in our case study

- **Shape coercion procedure is very sensitive**

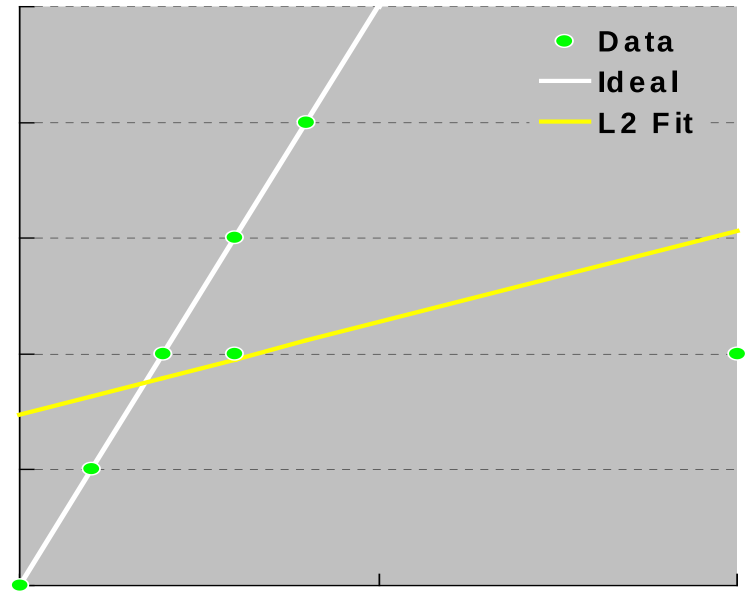
$$x_i = X_m + Pb_i$$

$$db = P^T dx$$

$\rightarrow$ provided by intensity model

•Designed for computation speed in 1995 (Pentium I) with 2D cases studies as reference

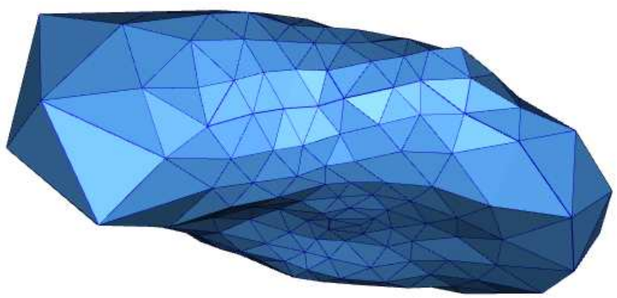
•Very sensitive to training set outliers, more frequent in 3D



- **Prototype can only be deformed on landmarks positions**

• scattering of landmark observes shape variability inferred by MDL simplex optimization

• shape coercion only works with corresponding landmarks



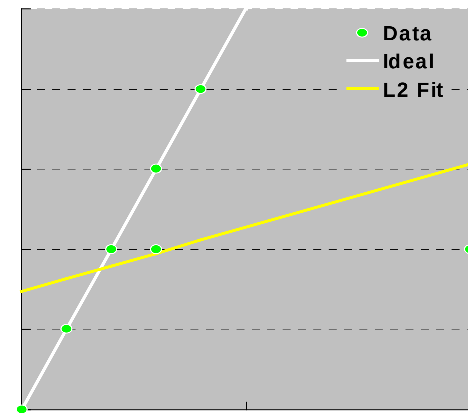
Landmarked putamen (258 ldks)

Mike Rogers and Jim Graham: ***«Robust Active Shape Model Search»***, ECCV 2002.

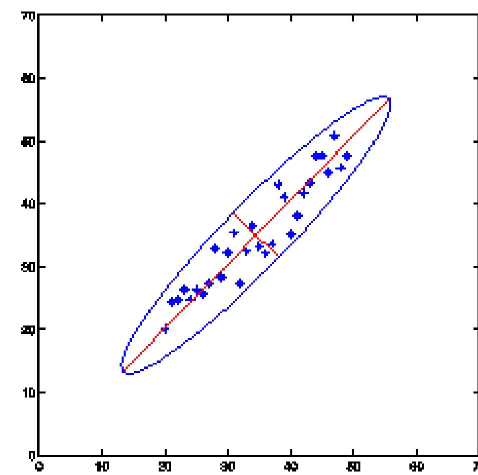
Active Shape Model

- **Workaround:** ***outliers elimination or neutralization in shape space [1]***
  - Search for analytic solution
  - search for closest amendment leading to target
  - assumes previous hypothesis is already good

$$db = P^T dx$$



- **Proposed solution:** ***find any close solution in Euclidean space***
  - at each iteration, search for a *close enough* shape instance
  - use Allowable Shape Domain properties
  - multi-scale search: close solution found within 100 iterations



$$x_i = x_m + P\, b_i$$

x_i

target

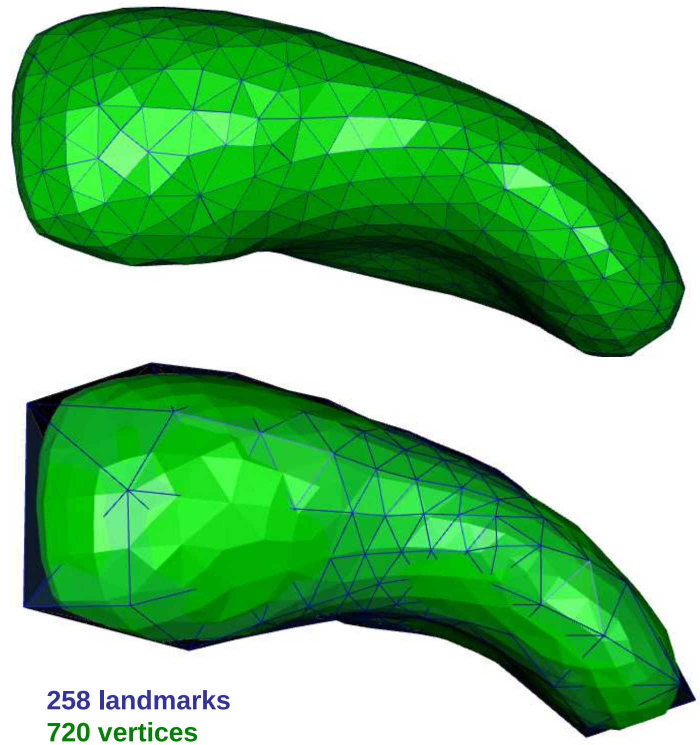
Procrustes distance O(n)

[1] Mike Rogers and Jim Graham: ***«Robust Active Shape Model Search»***, ECCV 2002.

Active Shape Model

Improving mesh resolution and degree of freedom

- ***Landmarked mesh improved by resolution increase***
  - Very fast implementation: ***Qslim*** [1]
  - Mesh can now be deformed in any direction
  - « Organic-shaped » thanks to smoothing
  - Improved mesh can be considered ***as dual*** to landmark mesh



- ***Influence on shape estimation procedure***
  - No more correspondence on vertices

    → Hausdorff distance $O(2n_1n_2)$ replaces Procrustes $O(n)$
  - Very efficient implementations (very relevant problem in CG): ***Mesh*** [2] is >5x faster
  - Significant accuracy increase for reasonable computational cost

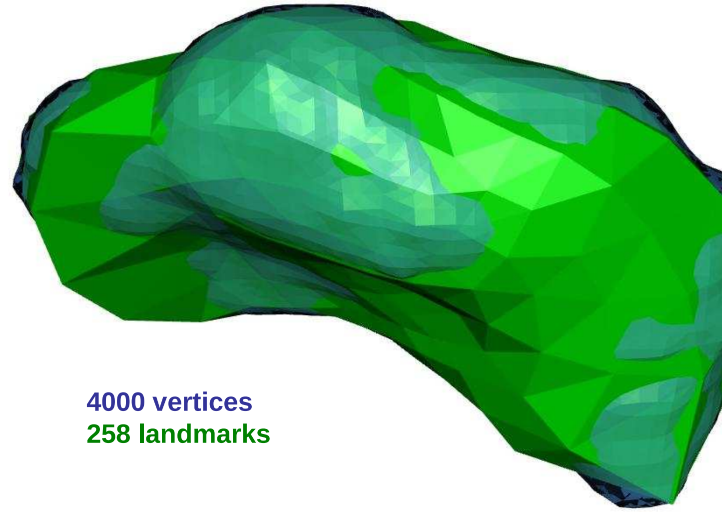
[1] Kircher, Garland: « ***Progressive Multiresolution Meshes for Deforming Surfaces*** », ACM/Eurographics Symposium on Computer Animation, 191—200, 2005

[2] Aspert, Santa Cruz, Ebrahimi: « ***MESH: Measuring Error between Surfaces using Hausdorff distance*** », Proceedings. of IEEE ICME, I:705—708, 2002

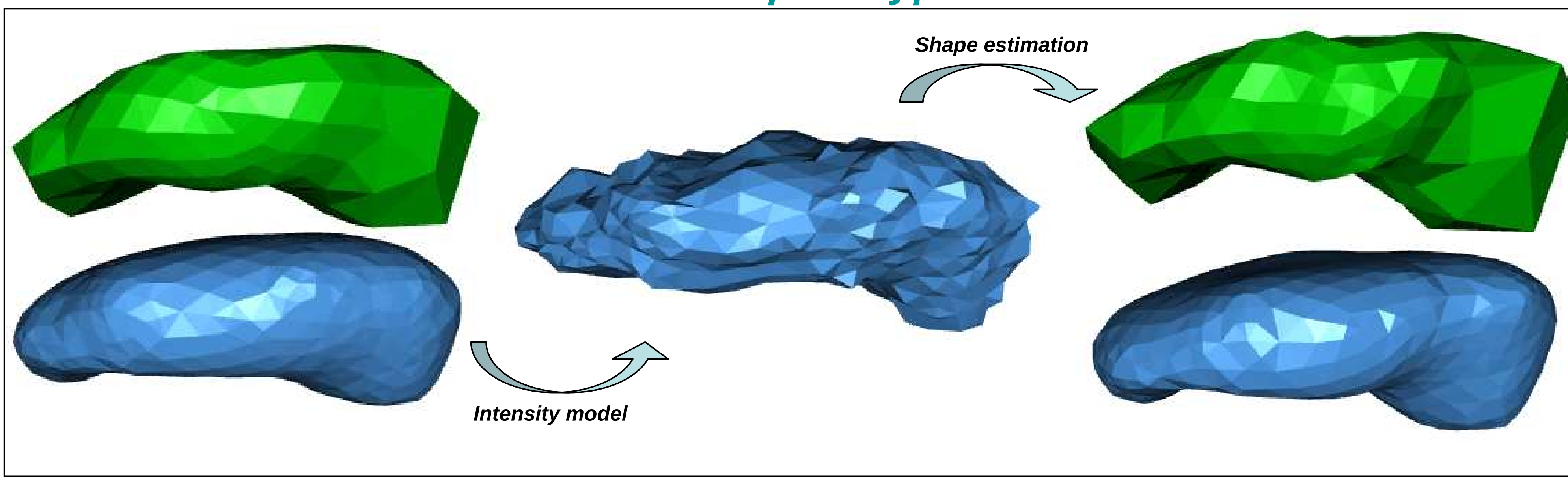
Active Shape Model

Overview of improved ASM

- ***Breakthrough:* shape estimation now works for any mesh (representing a shape instance)**
  - we can estimate the initial shape prototype from atlas registration
  - mean shape is actually arbitrarily far from this solution



- ***One Iteration of the ASM from this prototype***



Active Shape Models revisited in 3D:

- New method is relevant due to recent advances in Computer Graphics (1995-2007) and CPU/Memory improvements

Time & accuracy benchmark for the improved shape estimation:

Test shapes	1	2	3	4	5	6	7
Std. method error	5.3	8.0	4.8	3.55	6.5	7.2	5.9
Time (s)	1	1	1	1	1	1	1
Proposed method error	2.5	1.5	2.1	1.2	0.8	1.3	2.2
Time (s)	512	603	540	523	607	561	533

Unit: % of the shape instance bounding box. Shape instances selected randomly

Possible Improvements:

- standard I/O optimization (program prototype is script-based)
- low-level optimization using specialized GPUs (CUDA)

The end…

Slides & publications:

http://www.vectraproject.com/These/publis.html

Contacts:

Team GREYC Image: http://www.greyc.ensicaen.fr/EquipeImage