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SEGMENTATION OF ANATOMICAL STRUCTURES FROM 3D BRAIN MRI USING AUTOMATICALLY-BUILT STATISTICAL SHAPE MODELS

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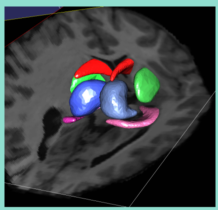
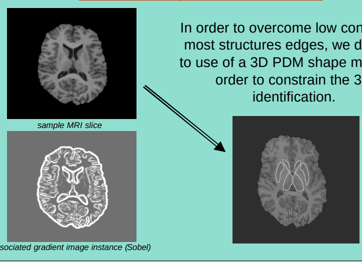
I - Introduction

Initial Target



Achieve automatic identification of anatomic structures from a 3D Brain MRI volume.

Brain MRI Specific Problems



In order to overcome low contrast at most structures edges, we decided to use of a 3D PDM shape model in order to constrain the 3D identification.

Proposed Method Overview

We need automatic methods for:

- 3D PDM building.
- structure identification using 3D PDM.

Establishing a 3D PDM demands:

- a training set of 3D instances of structure of interest.
- the relevant annotation of each instance by corresponding landmarks.

Specific context of our method:

Neither prior structure instances nor annotations are available.

II - 3D PDM Building of Brain MRI Anatomical Structures

Patients MRI database + **Anatomical atlas**

- Brains pre-alignment *(rigid registration, AIR 5).* (a)
- Atlas projection *(warp registration, AIR 5).* (a to b)
- *Visual quality check.*

Volumic structures database (b)

Polygonal transformation (b to c)
(marching cubes & decimation, VTK).

Surfacic structures training sets (e, f)

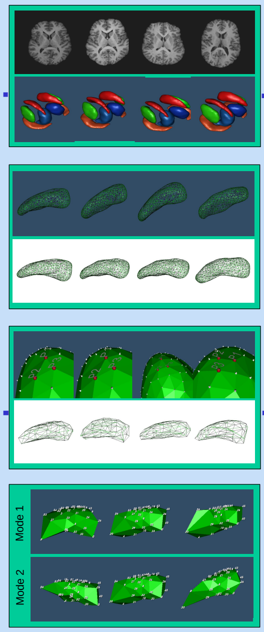
- Structures pre-alignement (c to d)
  (rigid Iterative Closest Point registration, VTK).
- *Reference triangle selection.* (e)
- Automatic landmarking (**SM2 API [3]**). (e to f)

Landmarked structures (f)

- Structures pre-alignement
  (rigid Procrustes, VTK).
- Covariance matrix + PCA

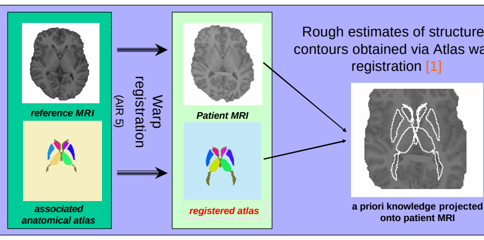
PDM models of structures (g)

Results: Inferred PDMs raise consistent & distinct variation modes for structures of interest.



(a) Structure Estimation through Atlas Projection

A priori information about structure countour geometry and localization



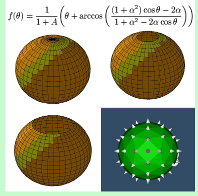
Rough estimates of structures contours obtained via Atlas warp registration [1]

(b) Automatic Landmarking Overview

A Simplex-minimization framework, considering many training set annotation hypotheses, converges to the most relevant one through quality evaluation of each derived PDM *(Davies et al.[2], Kildeby et al.[3]).*

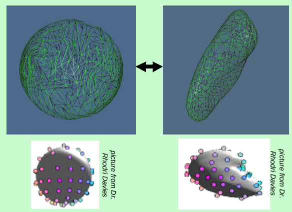
Step 1: generate sphere landmarkings

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



Sphere reparameterization by cumulative distribution fonction of Cauchy Kernels need only few parameters, favouring simplex optimization.

Step 2: backproject current landmarks to structure



Spherical mapping of each structure optimizing angle & area preservation.

Step 3: quantify the quality of current PDM

MDL(PDM) = MDL(*mean shape*) + MDL(*significant modes*) + MDL(*residual modes*)

A Minimum Description Length (MDL) based objective function evaluates current PDM, balancing its generalization ability with correctness. Its minimization enables the simplex to converge to an « optimal » PDM.

III – A New Intensity Model To Guide PDM Segmentation

Difficulties:

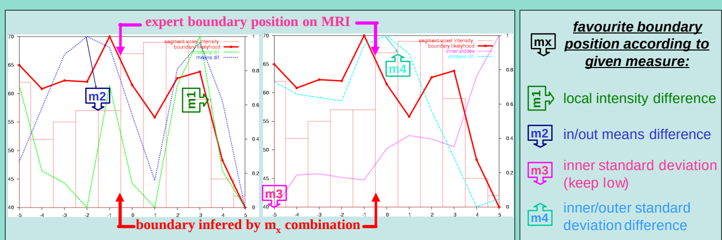
- Since the training set was just registered (and not determined by an expert), we cannot statistically learn the positions of a given landmark on its boundary along the set of MRI images: *a new approach must be found.*
- Due to noise and low contrast in MRI images, any measure might fail whatever our efforts.

Key ideas:

- Use measures without training set prior knowledge, emphasizing exactness on present MRI.
- Compensate low MRI quality and measure reliability in multiplying measures.

Case study: locate boundary position for one landmark on the left Putamen

- Seek for boundary position from the current landmark position along normal direction to the surface.
- Choose position on corresponding segment of voxels maximizing differences between inside & outside:

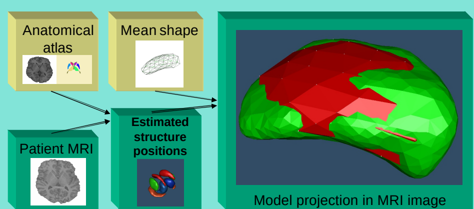


Results: *method correctness on all landmarks of the Putamen case study*

%	intensity Δ	means Δ	inner std-dev	outer/inner std-dev Δ	overall
1st peak *(success)*	33	50	64	45	75
lower peak	45	33	11	33	15
critical miss	22	17	25	22	10

Perspective: MRI Segmentation through joint Use of Shape and Intensity Models

Step 1: Projecting mean shape model into patient MRI coordinates



Step 2: Iterative adaptation of mean shape model to patient MRI

Iterate until idempotence:

1. Locally search best movement for each landmark along normal direction.
2. Infer and apply rigid movement for current shape model.
3. Infer shape parameters modification to best suit residual moves.

Difficulties:

- Estimation of optimal shape parameters.
- Shape model « crushes » if locally too far from estimated boundary.

Some references:

[1]: **Jing-Hao Xue,Su Ruan, Bruno Moretti, Marinette Revenu, Daniel Bloyet,** *« Knowledge-based segmentation an labeling of brain structures from MRI images »*,Pattern Recognition Letters, 22, pp 395-405, 2001.
[2]: **Rhodri H. Davies, Carole J. Twining, Tim F. Cootes, John C. Waterton, Chris J. Taylor**, "A Minimum Description Length Approach to Statistical Shape Modeling", IEEE Transactions on Medical Imaging, 21(5), May 2002.
[3]: **Allan Reinhold Kildeby**, "Building optimal 3D shape models", Master's Thesis, Informatics and Mathematical Modelling, Technical University of Denmark, DTU, Supervisor: Rasmus Larsen, 2002.