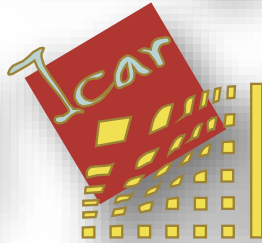


# Automatic segmentation of 3D high-resolution images by deformable models



(1)

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(2)

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(3)



(4)



# Motivations

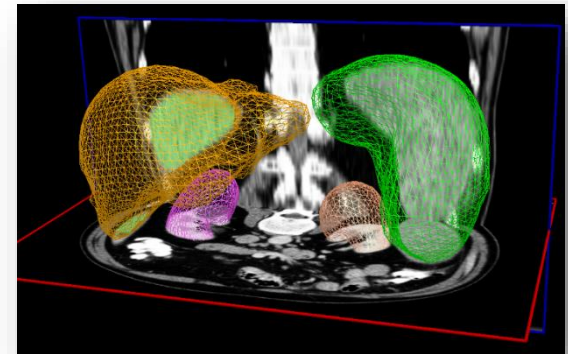
Segmentation (e.g. delineating a Region of Interest) is a **major challenge** in 3D image processing.

- Manual method: delineate slice after slice
  - Tedious task (especially for huge data as  $\mu$ -CT);
  - Operator-dependent.
- Automatic methods:
  - Often based on low-level processing (e.g. thresholding);
  - But becomes very complex when:
    - poor contrast;
    - fuzzy boundaries (artefact, fractured parts...)

→ **Idea: use some knowledge on the shape** to guide segmentation:

- Shape regularity (e.g. smooth);
- Shape characterization;
- Shape + variability characterization.

→ **3D deformable model**



# Principle of 3D deformable models

- Take a **reference 3D mesh** of the structure;
- Define :
  - **External** constraints: “attraction” by **features** in the 3D image (e.g. image discontinuities);
  - **Internal** constraints: keeping the shape **regular** or **close** to a specific shape (up to some specific variability).
- **Deform** iteratively **the 3D mesh in the 3D image** w.r.t. **both constraints**.

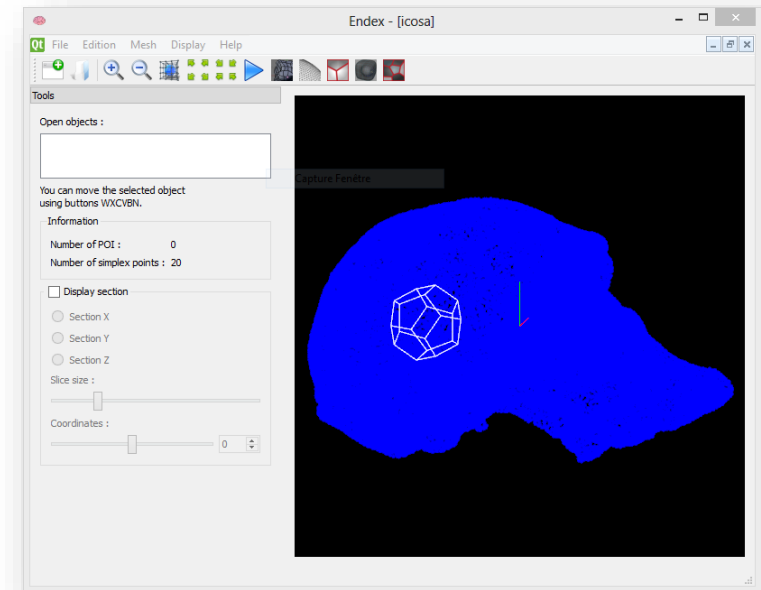
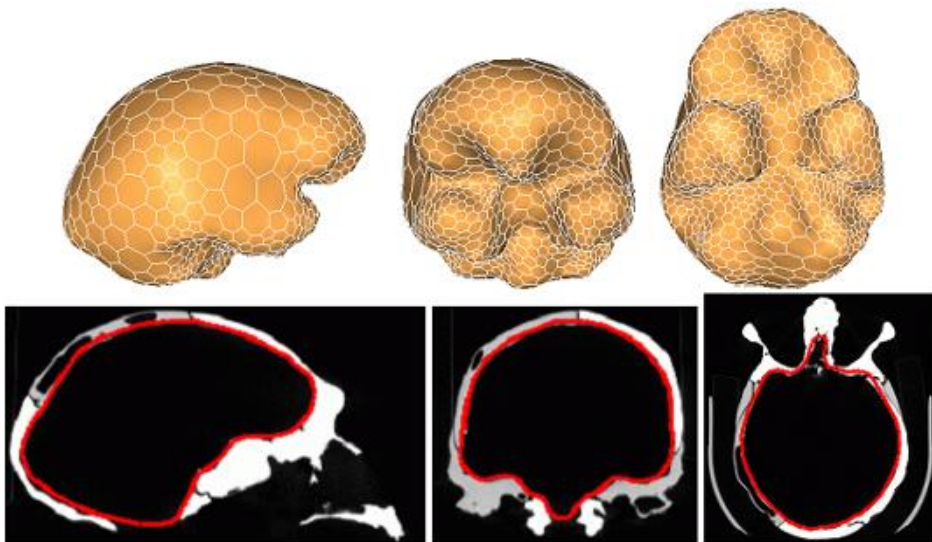
[C. Xu, D. L. Pham, and J. L. Prince, "Medical Image Segmentation Using Deformable Models," *Handbook of Medical Imaging -- Volume 2: Medical Image Processing and Analysis*, pp. 129-174, edited by J.M. Fitzpatrick and M. Sonka, SPIE Press, May 2000]

→ 2 examples with different implementations

[T. McInerney T, D. Terzopoulos. "Deformable models in medical image analysis: a survey". *Med Image Anal.* 1996 Jun;1(2):91-108]

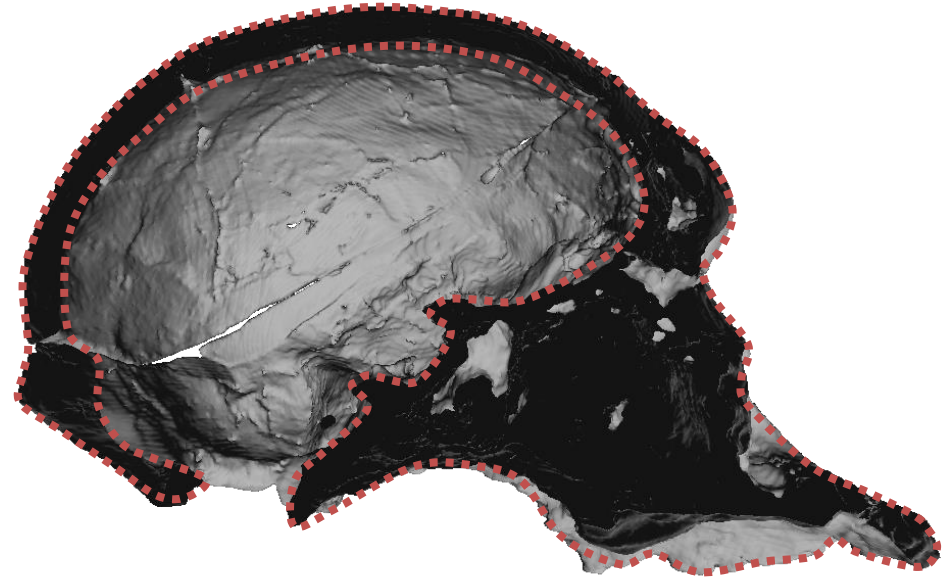
# Example 1 : segmenting endocranium in CT images

- Endocranium = inner part of the skull:
  - Gives a 3D rough representation of the brain shape;
  - Great interest, in particular in paleo-anthropology.
- Skull in CT image: good contrast.... but non-closed structure
  - *boundaries are non always defined.*



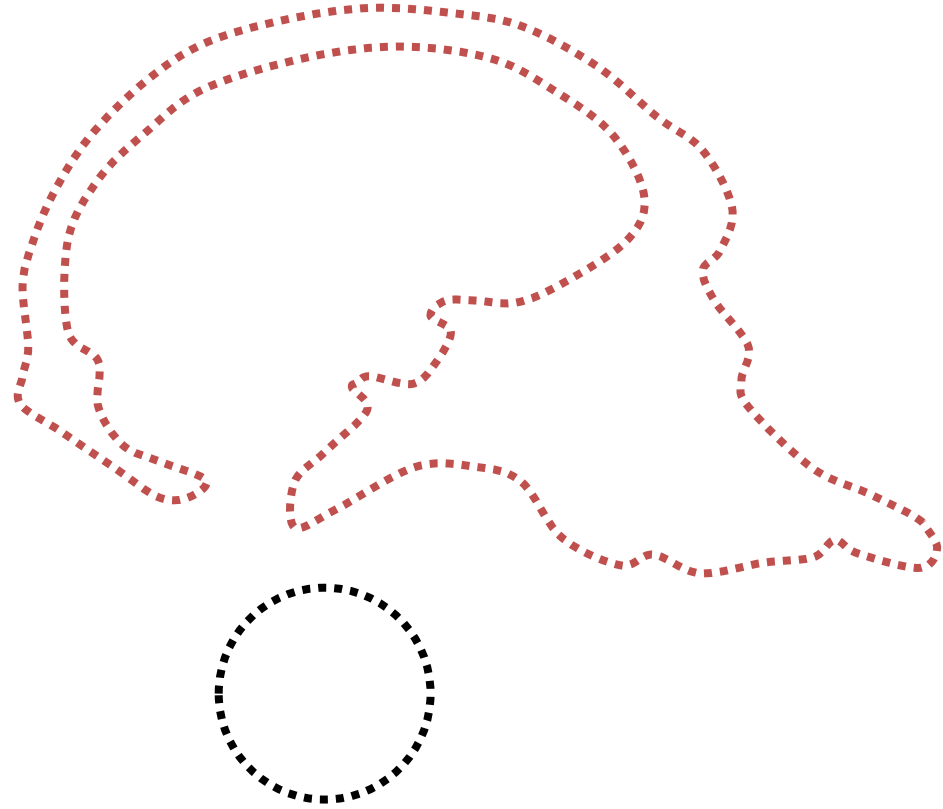
# Principle of the method

- Features = skull surface (e.g. by thresholding)



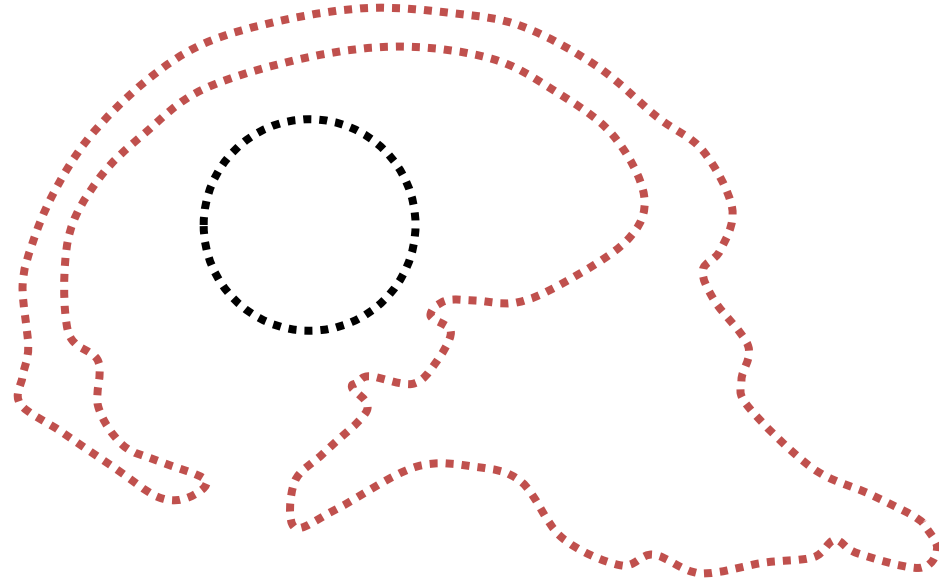
# Principle of the method

- Features = skull surface (e.g. by thresholding)
- Let a simple closed surface mesh composed of 3D vertices  $P_i$  (e.g. a sphere)



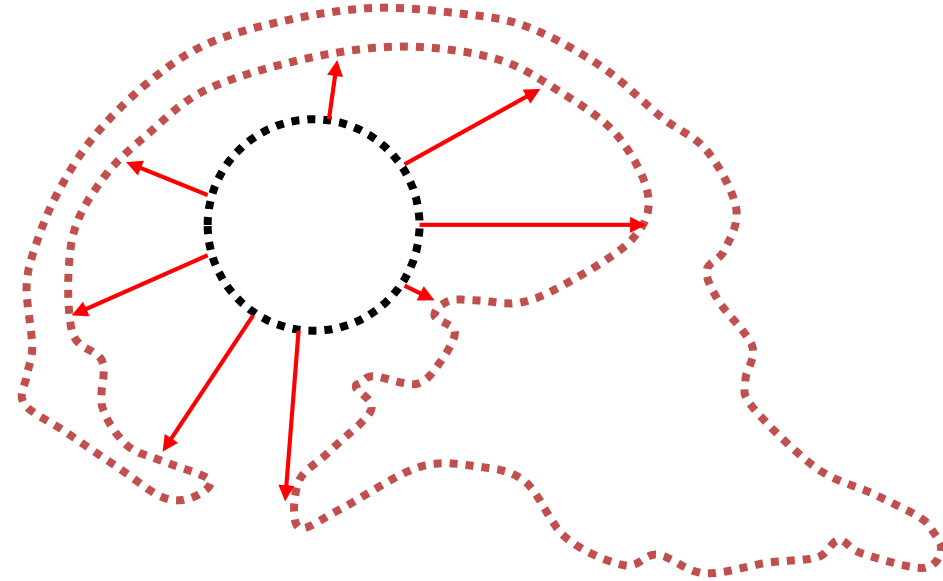
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- Features = skull surface (e.g. by thresholding)
- Let a simple closed surface mesh composed of 3D vertices  $P_i$  (e.g. a sphere)
- The surface mesh is initially positioned "in the middle" of the data



# Principle of the method

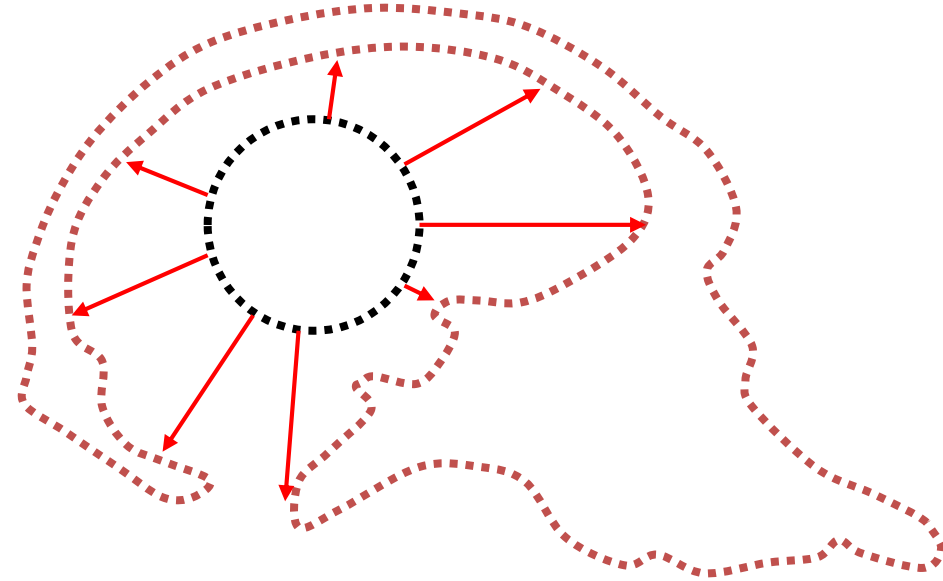
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- Let a simple closed surface mesh composed of 3D vertices  $P_i$  (e.g. a sphere)
- The surface mesh is initially positioned "in the middle" of the data
- This surface will deform under the influence of:
  - an external force  $F_{ext}$  which attracts the vertices  $P_i$  towards the data
  - an internal force  $F_{int}$  which tends to keep the surface smooth (e.g. curvature continuity)





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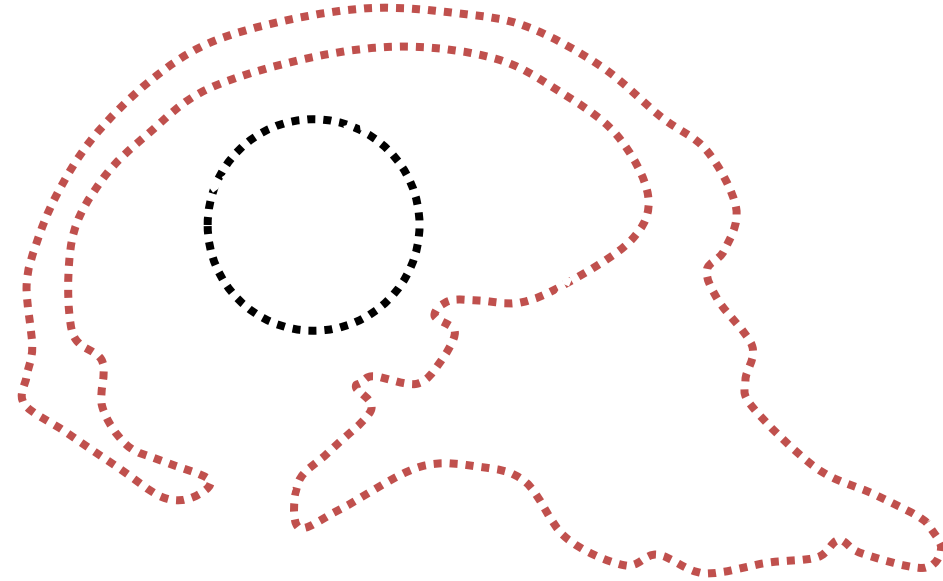


- At time  $t$ , all the vertices  $P_i$  follow the evolution law:

$$P_i^{t+1} = P_i^t + (1 - \gamma)(P_i^t - P_i^{t-1}) + \alpha_i \mathbf{F}_{int} + \beta_i \mathbf{F}_{ext}$$

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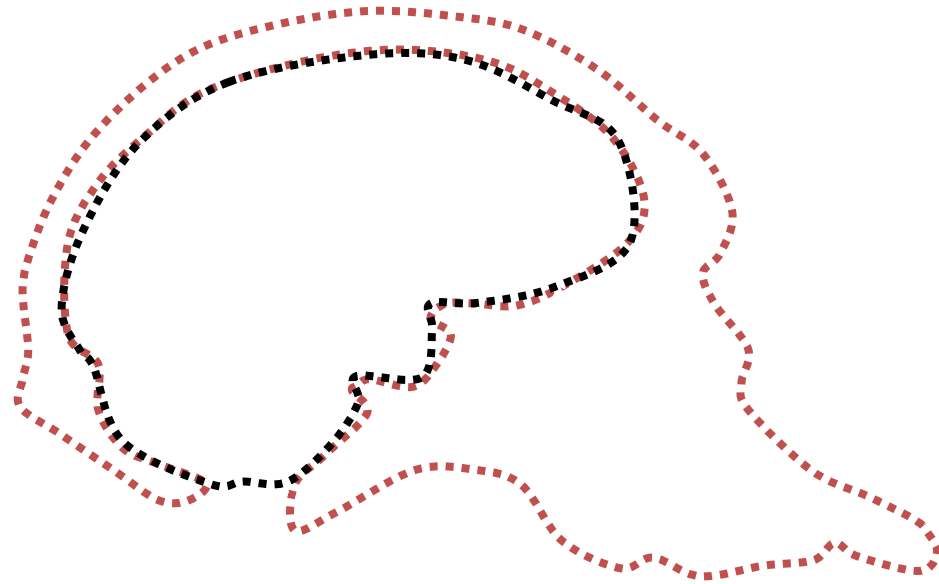
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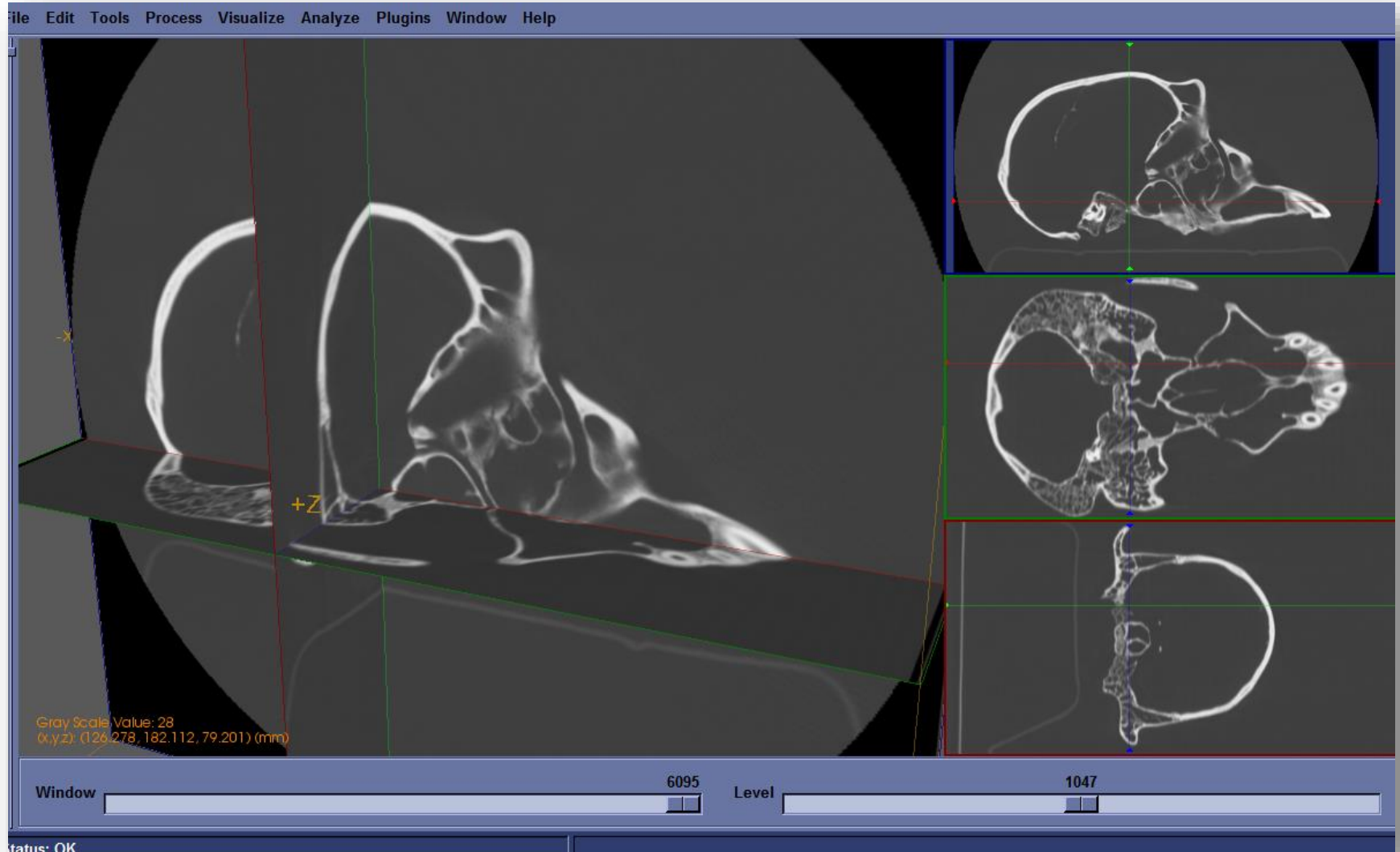
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- Iterate the process until the vertices  $P_i$  do not move anymore.
- Eventually, add more vertices in the mesh when the distance between the existing vertices becomes too large in order to recover the details.

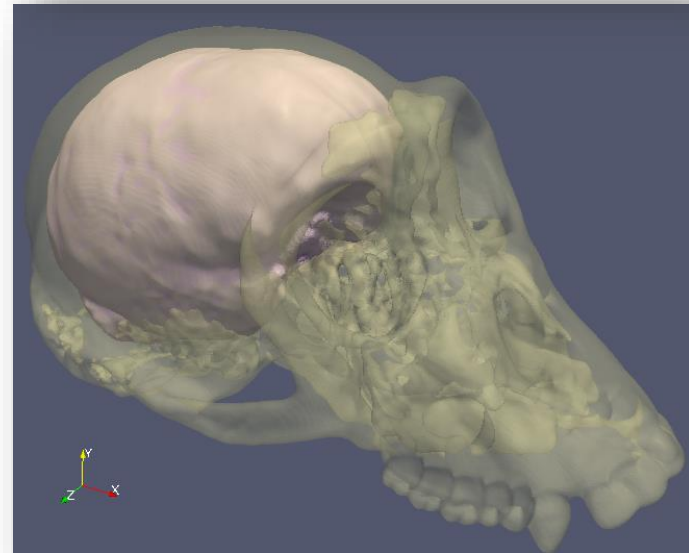
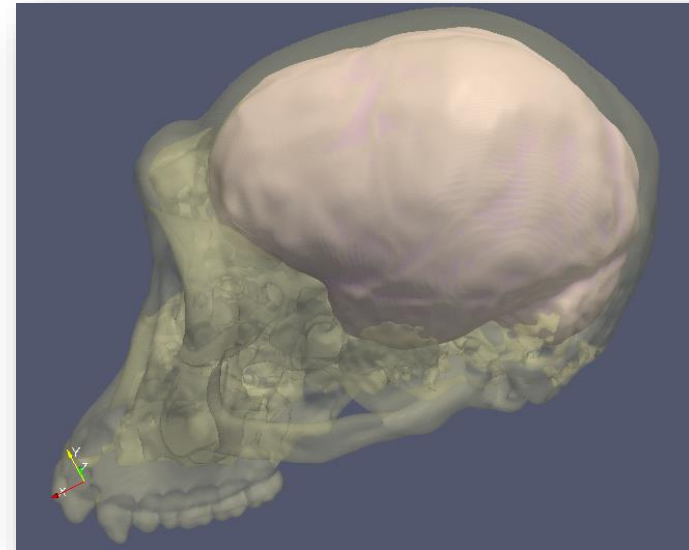
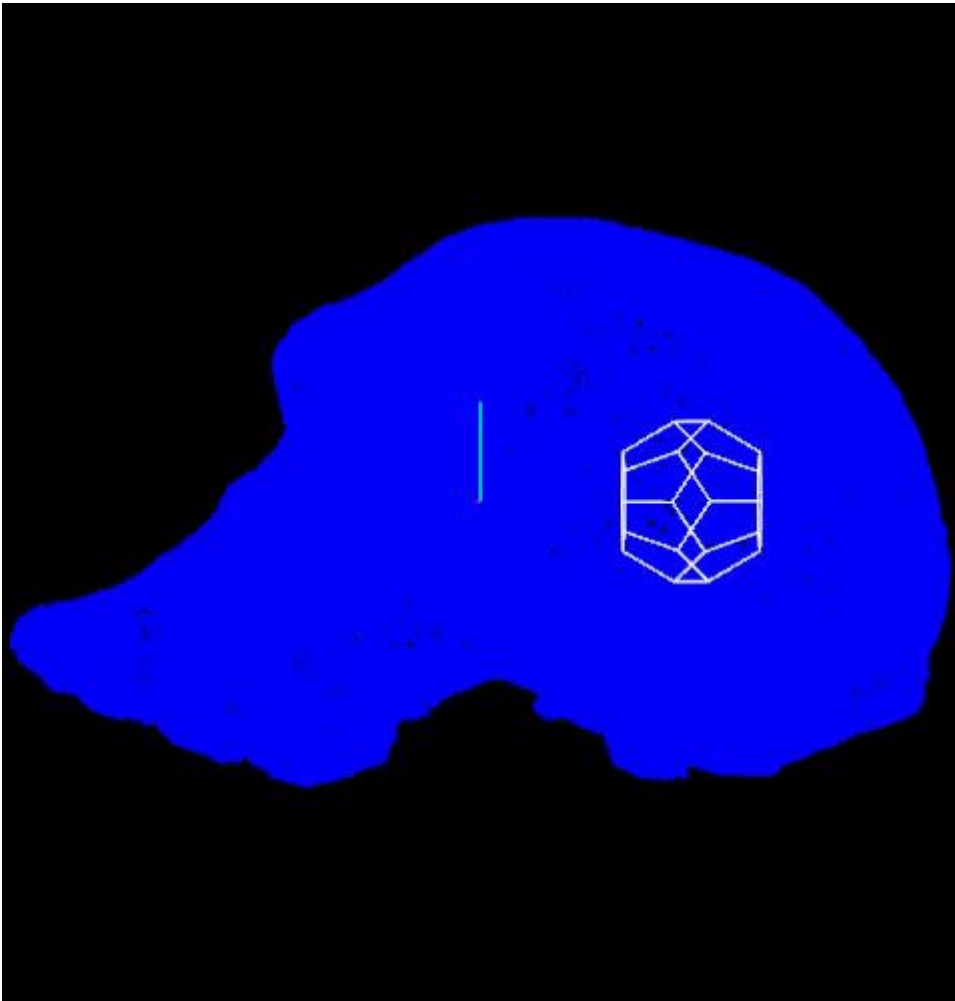
# Pan troglodytes

- CT-Scan of a skull: 209 slices of  $512 \times 512$  pixels
- Resolution:  $0.461 \times 0.461 \times 0.600$ mm



# Pan troglodytes

- Manual localization of the initial deformable surface;
- No more user interaction;
- Fast process (real-time video)
- Result mesh: 398,942 vertices / 797,880 faces

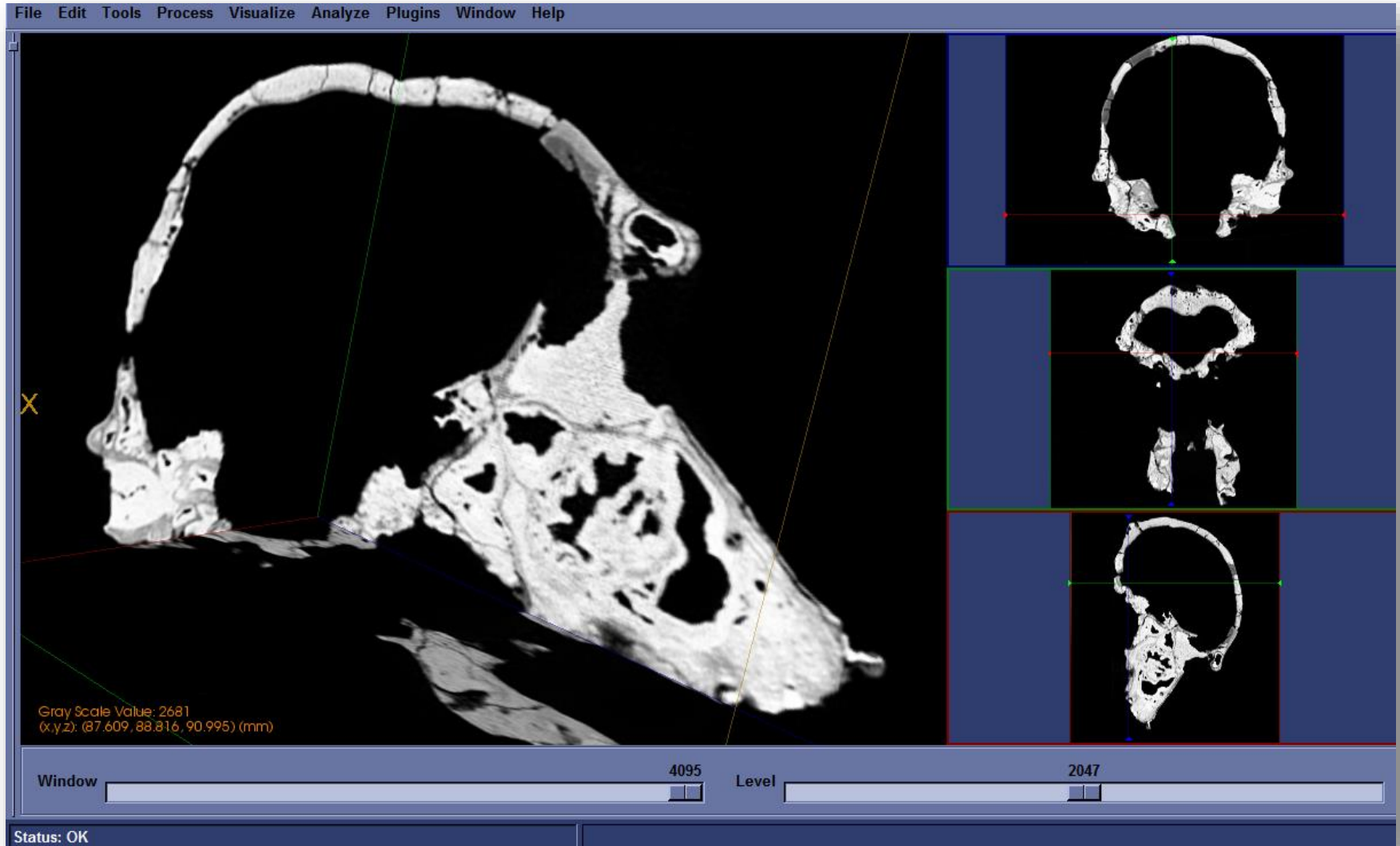




# Australopithecus africanus STS5

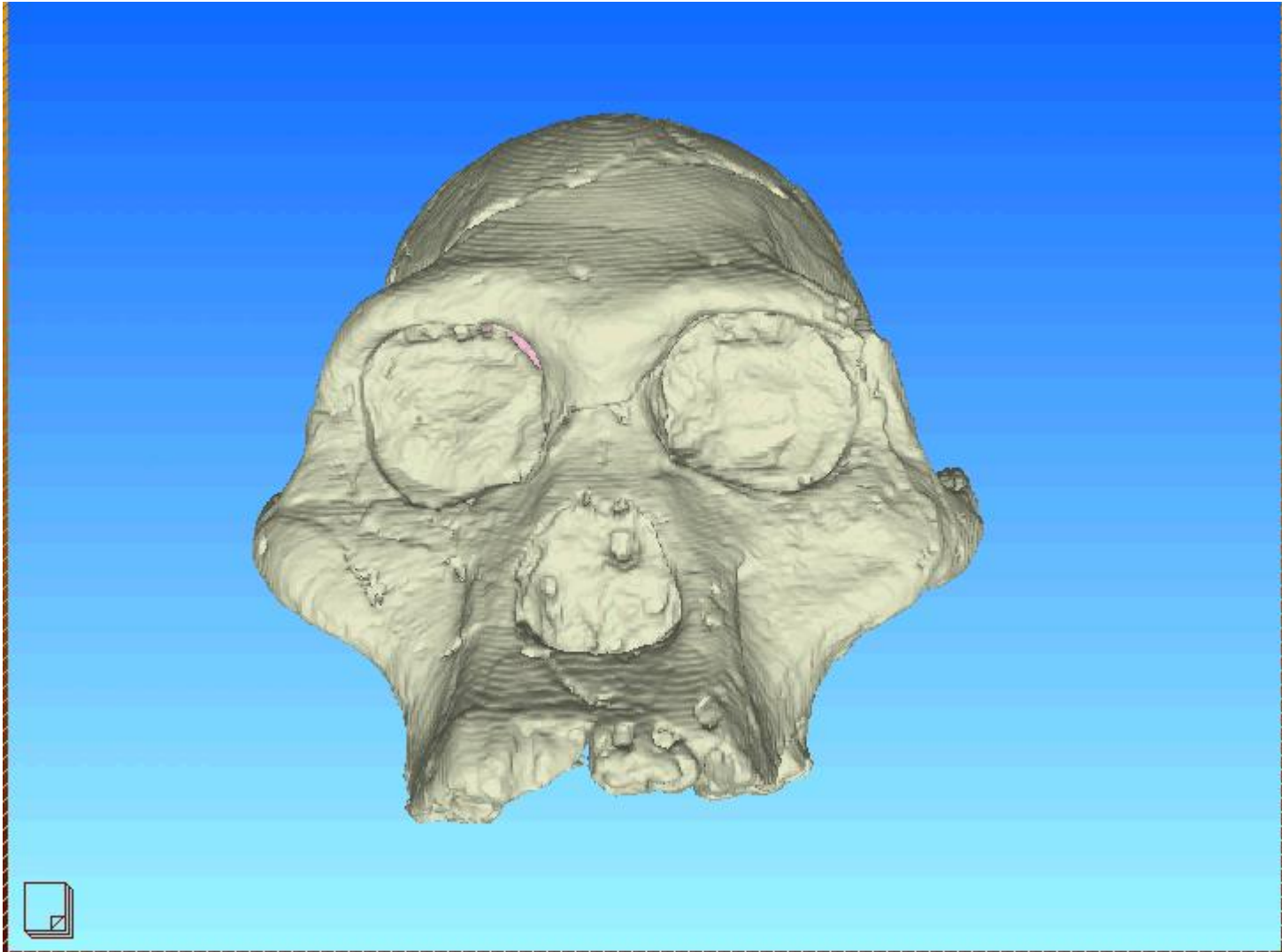
- CT-Scan of the fossil: 998 slices of  $512 \times 512$  pixels
- Resolution:  $0.348 \times 0.348 \times 0.200$  mm

*Thanks to S. Potze and Prof. F. Thackeray for providing data.*

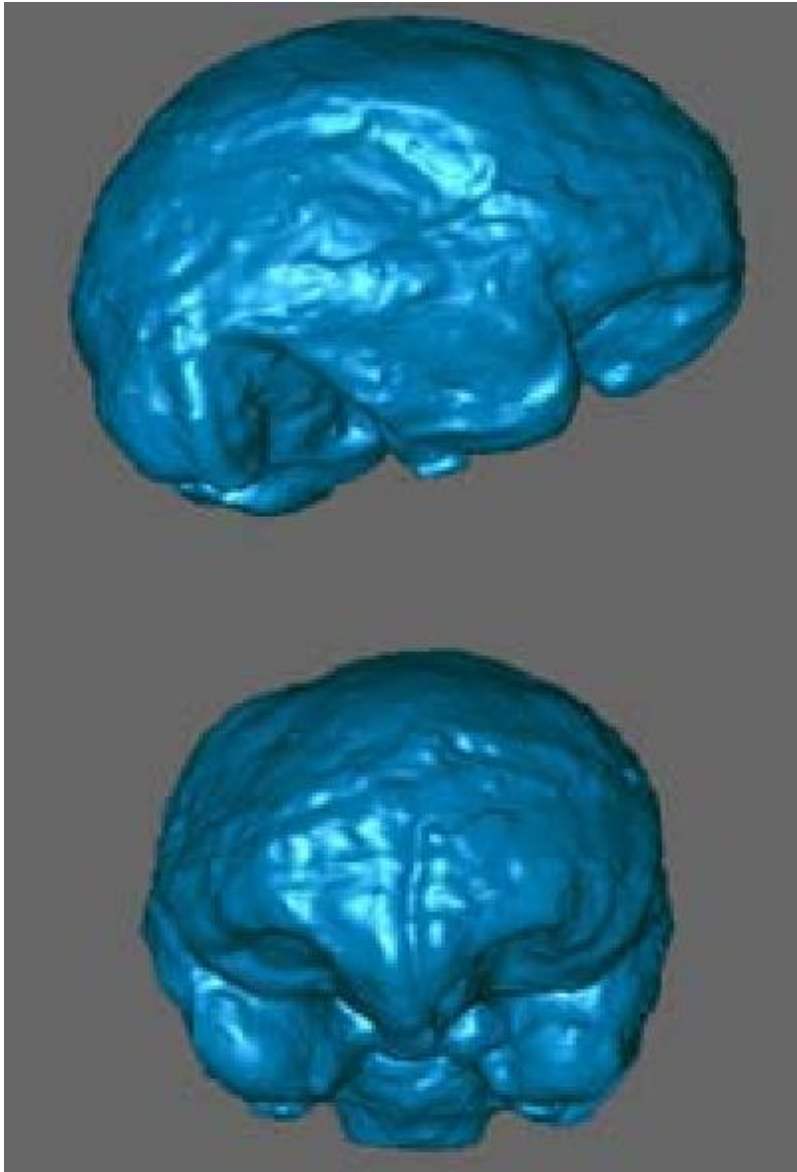


# Australopithecus africanus STS5

- Result mesh: 401,960 vertices / 803,916 faces

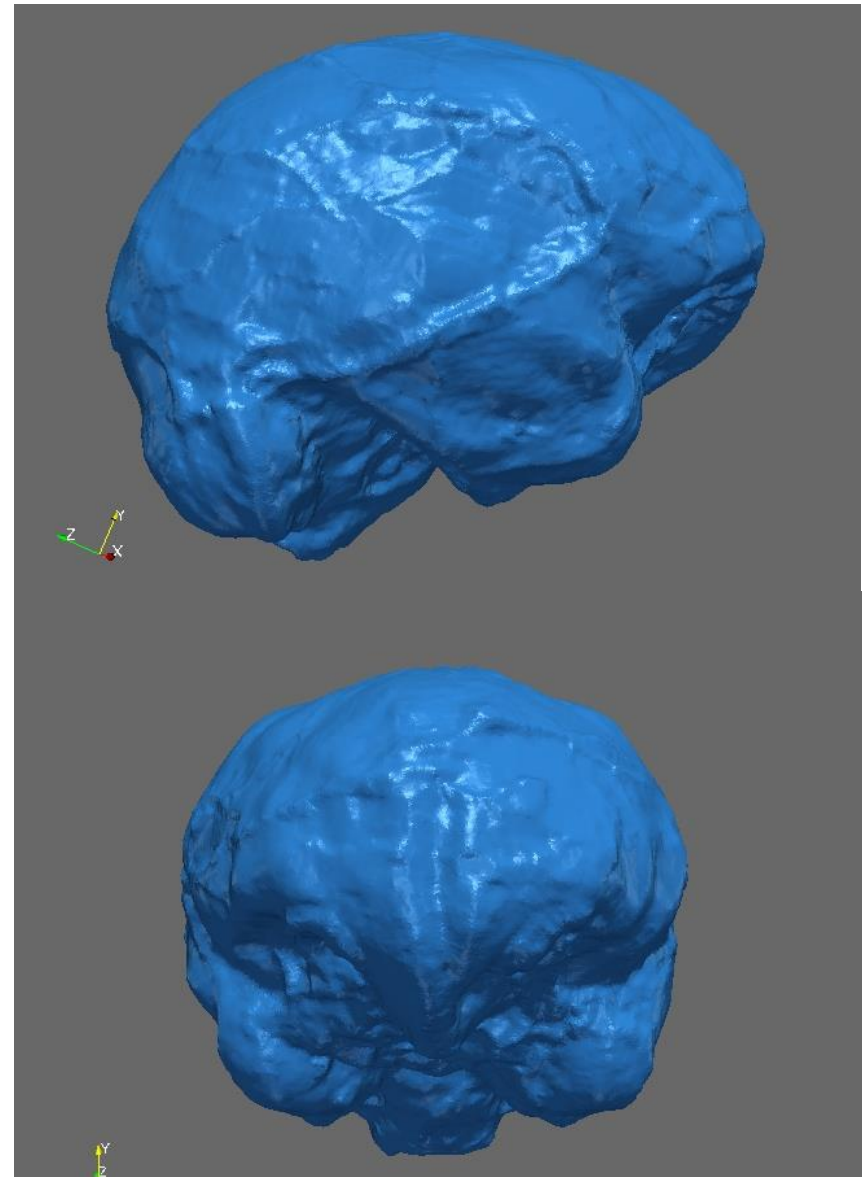


[D. Falk et al. "The Brain of LB1, Homo floresiensis". Science, 308, 242 (2005)] (473 cm<sup>3</sup>).



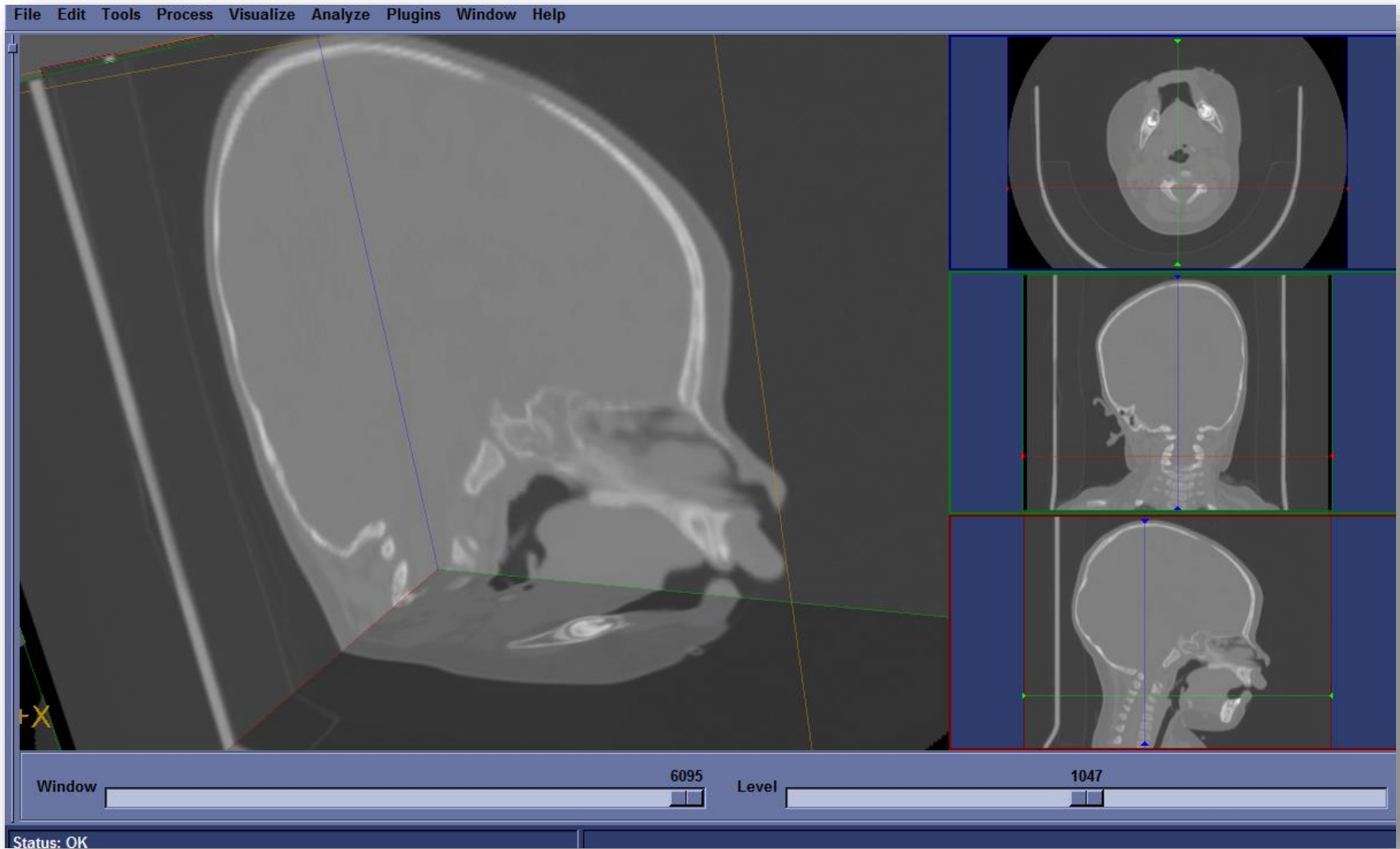
## Australopithecus africanus STS5

Our segmentation (476 cm<sup>3</sup>)



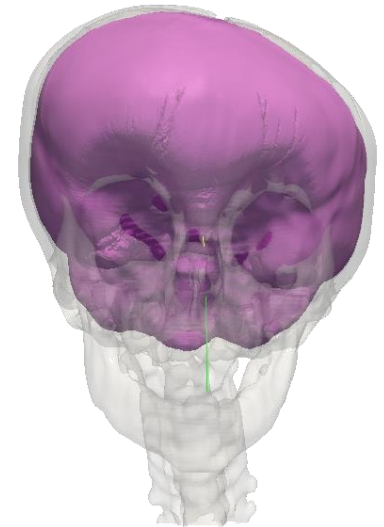
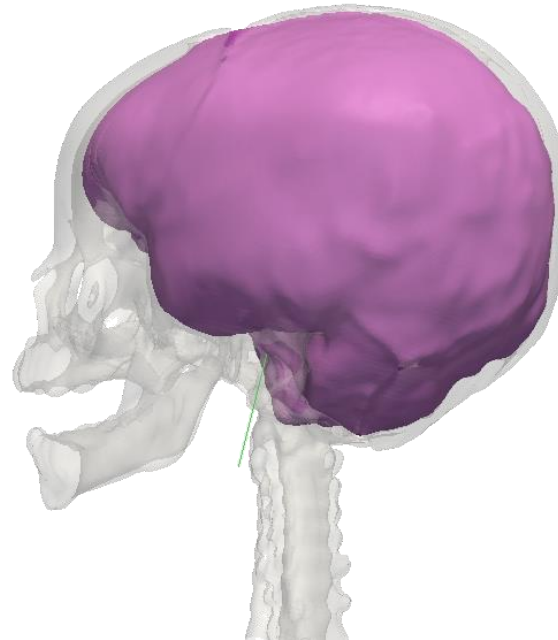
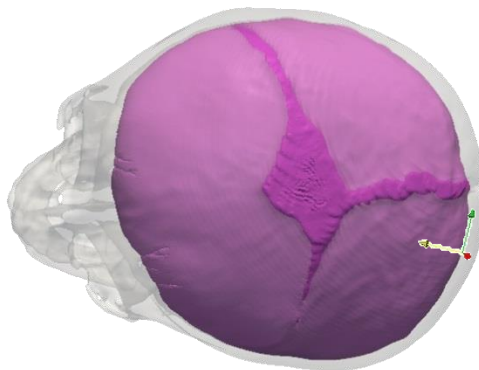
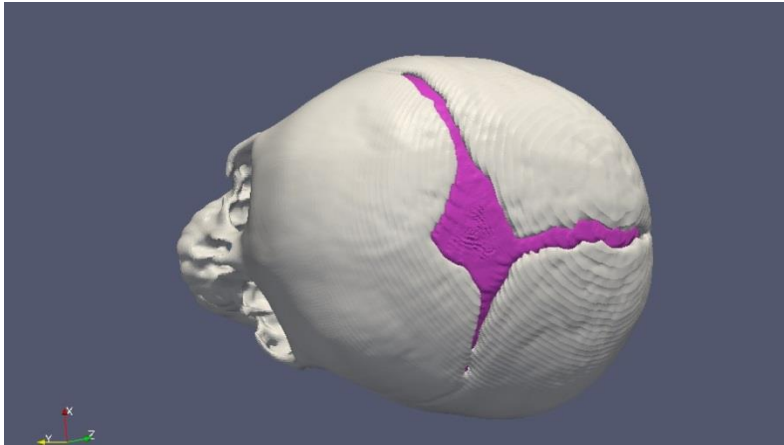
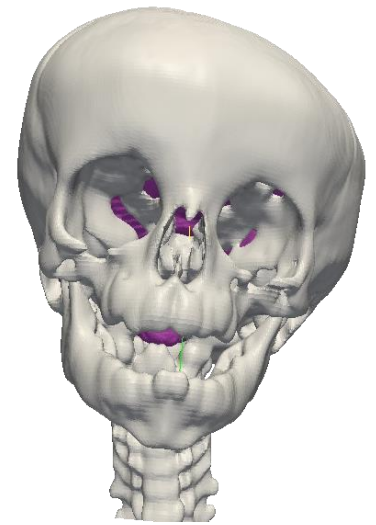
# In-vivo data

- CT-Scan of the head of a child affected by a plagiocephaly (asymmetrical distortion of the skull): 153 slices of  $512 \times 512$  pixels
- Resolution:  $0.488 \times 0.488 \times 1.250$  mm



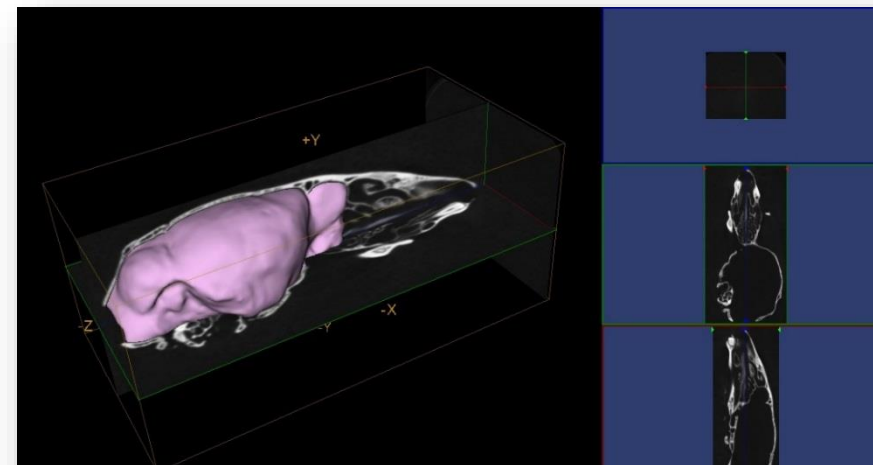
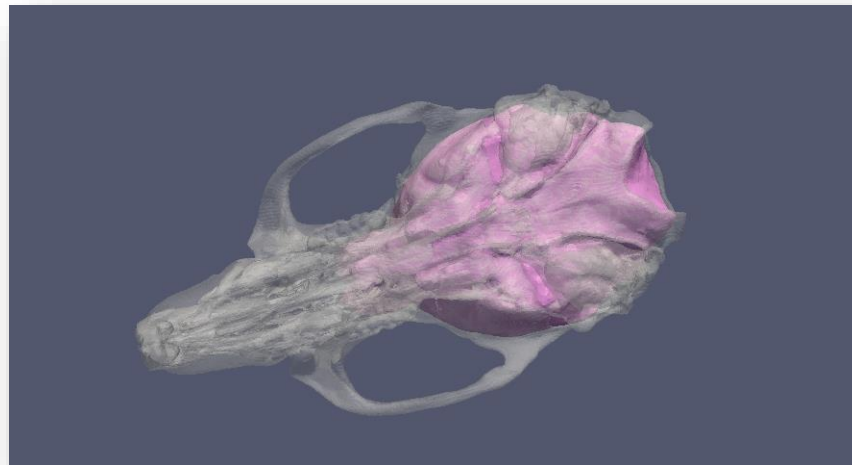
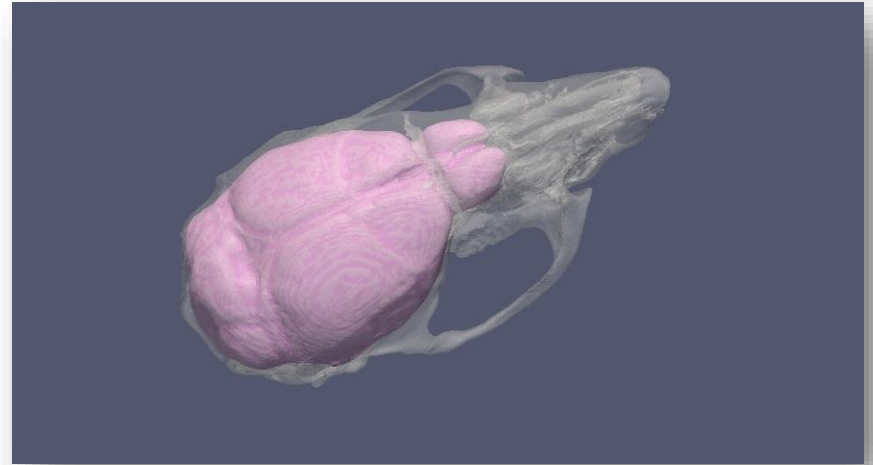
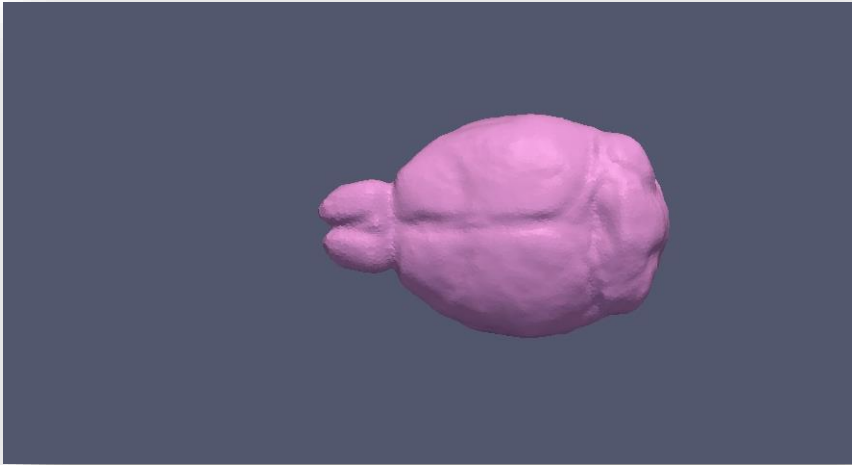
# In-vivo data

- Manage automatically the fontanelles;
- Result mesh: 364,721 vertices / 729,438 faces;
- Could be useful to analyze the 3D deformation of the endocranium and of the skull base.



# $\mu$ -CT data

- $\mu$ -CT-Scan of a mouse: 603 slices of  $329 \times 274$  pixels /  $0.0386 \times 0.0386 \times 0.0415$  mm
- Application in biomedical research (genetically modified mouse)



# Example 2: computer-aided recognition

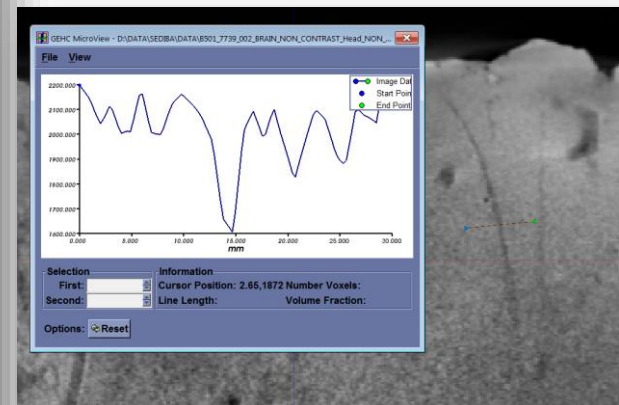
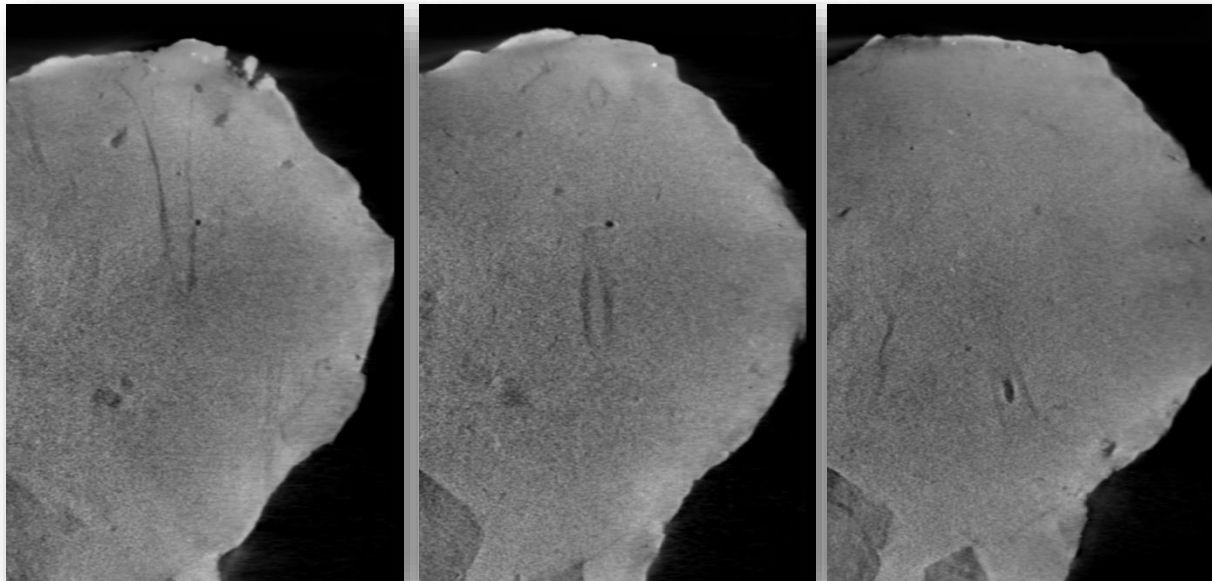


CT-Scan of a potential fossil-bearing block (512×512×1,139 voxels, 0.9766×0.9766×0.5 mm)..

Poor contrasted CT image with many artefacts → *unclear boundaries*

*Thanks to Prof. Lee Burger for providing data.*

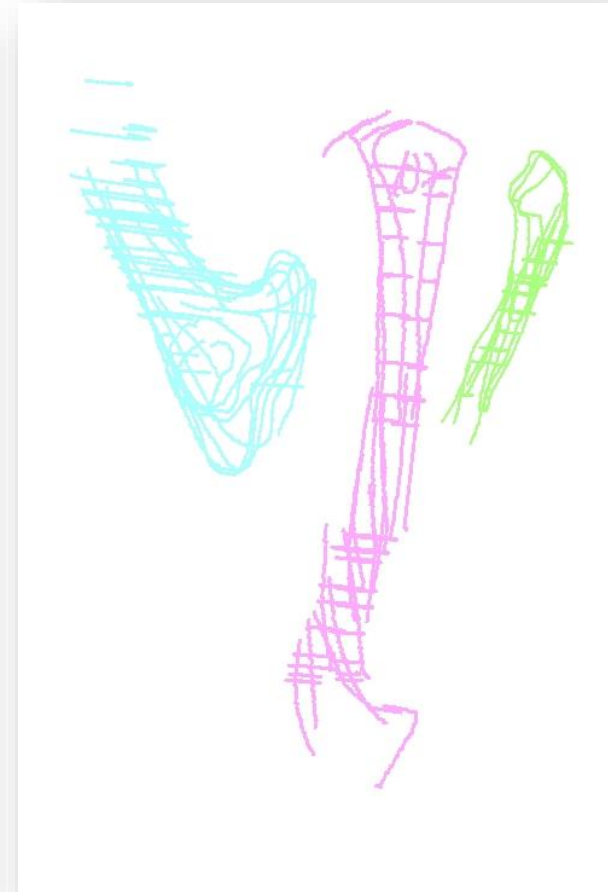
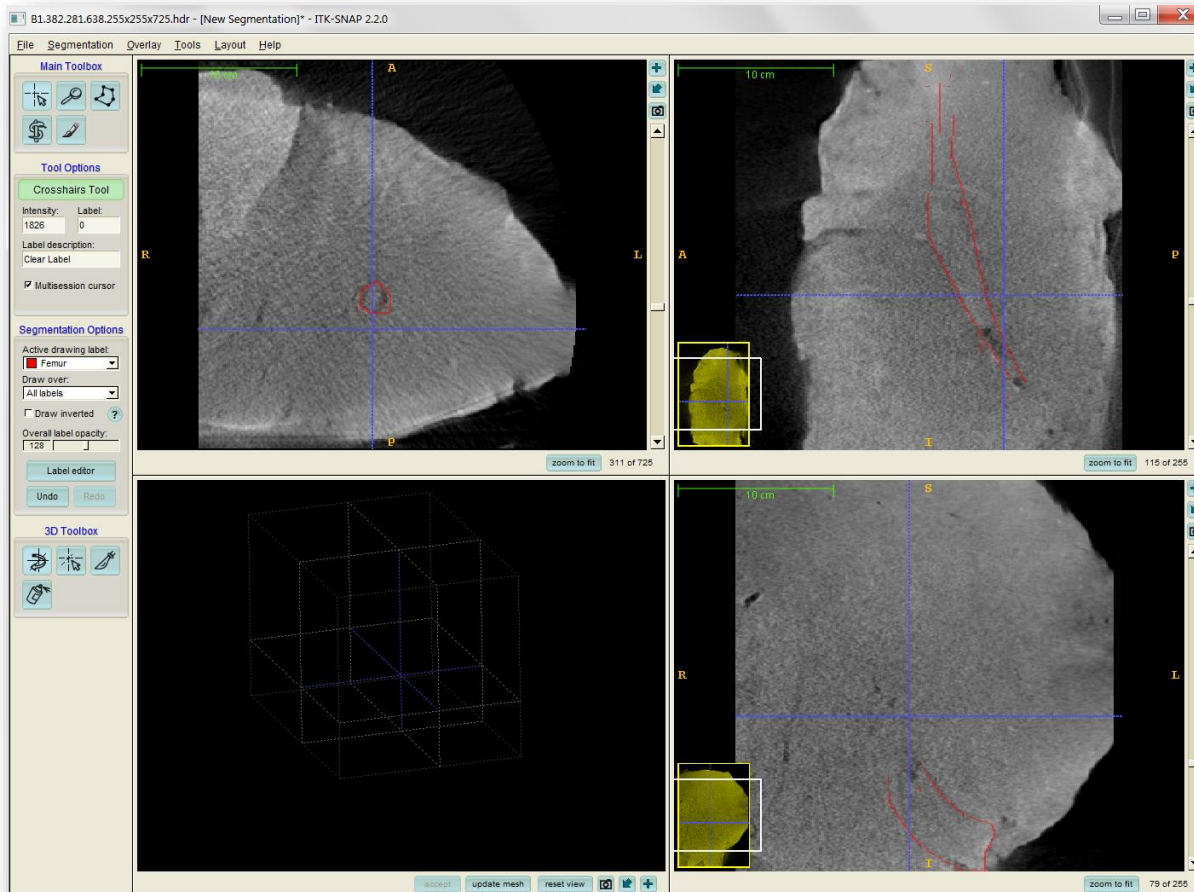
*See also “Virtual preparation of fossil bones from Cave deposit in the Cradle of Humankind” presented by Aurore Val yesterday.*



# Example 2: computer-aided recognition

→ Try to identify the bone:

➤ Define manually some features in the 3D image (<5 mn);





# Example 2: computer-aided recognition

- Use a 3D deformable surface of a given anatomical structure to fit features;

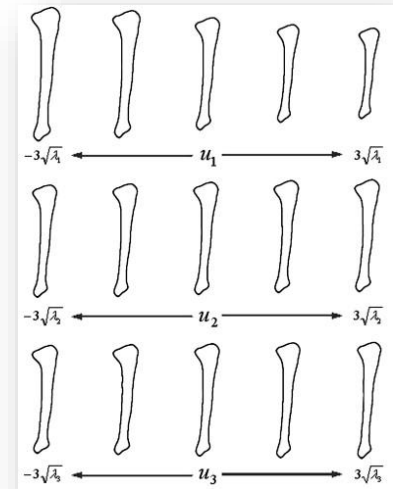
Shape characterization will be too limited in this case → **Shape + variability** characterization.

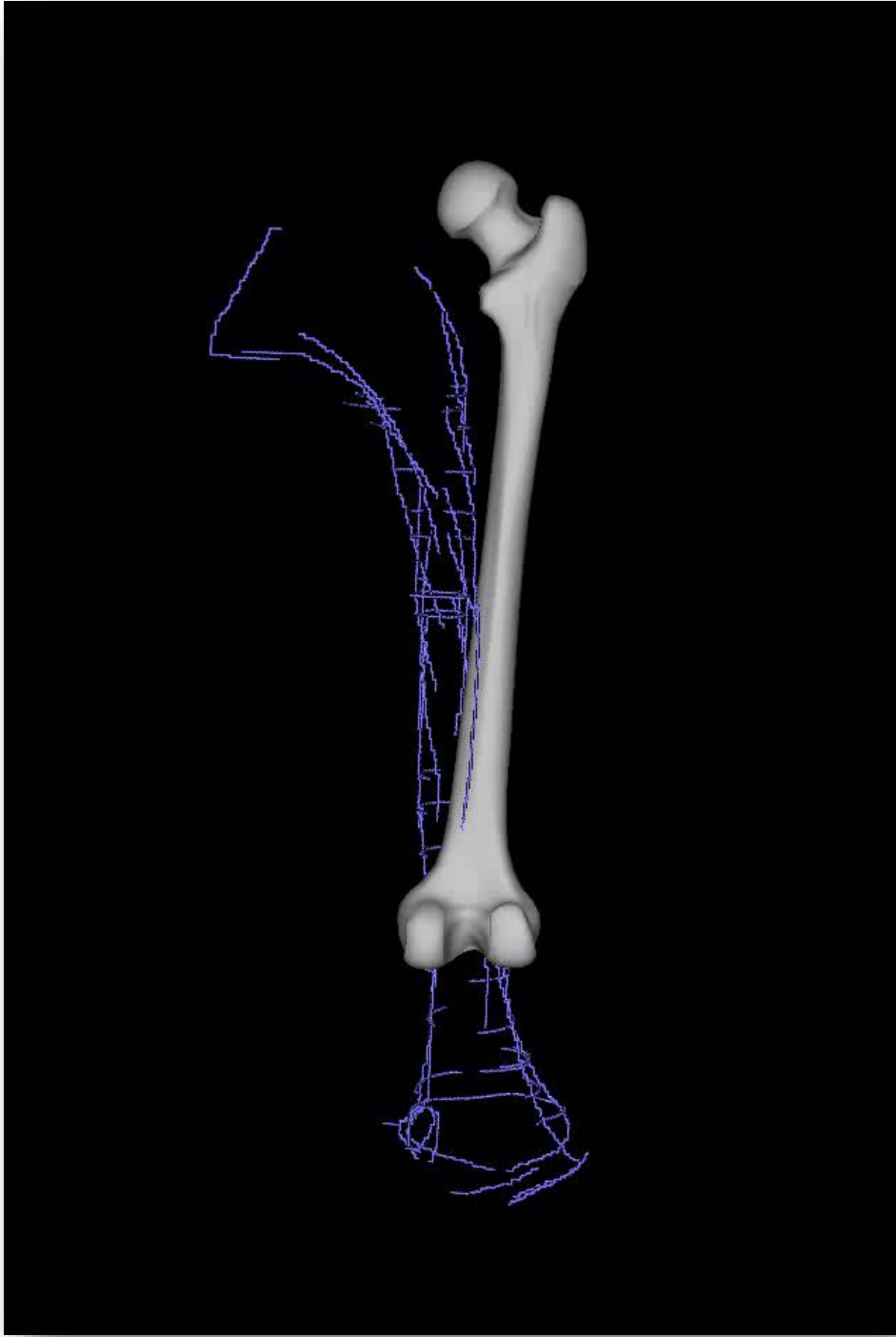
## 1. Creation of an average + variability model:

- Database of 3D meshes of the given anatomical structure;
- Register all the 3D meshes on a reference one;
- Compute an **average 3D mesh** by averaging vertex positions;
- Principal Component Analysis of all the differences w.r.t. to the average 3D mesh  
→ **Principal modes of variation and their variances.**

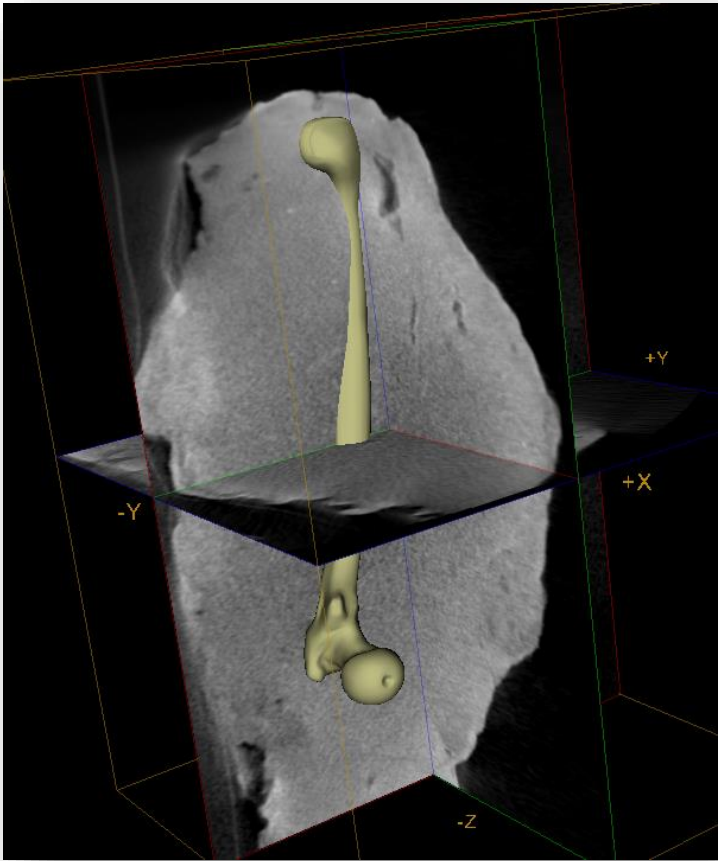
## 2. Using the deformable surface

- For each vertex of the 3D average mesh, find the closest feature;
- All correspondences → 3D transformation;
- Project this transformation on the  $n$  first principal modes  
→ **New transformation which takes into account the variability around the average shape.**
- Apply this transformation;
- Increase  $n$  in order to get a more detailed transformation;
- Iterate until it converges.



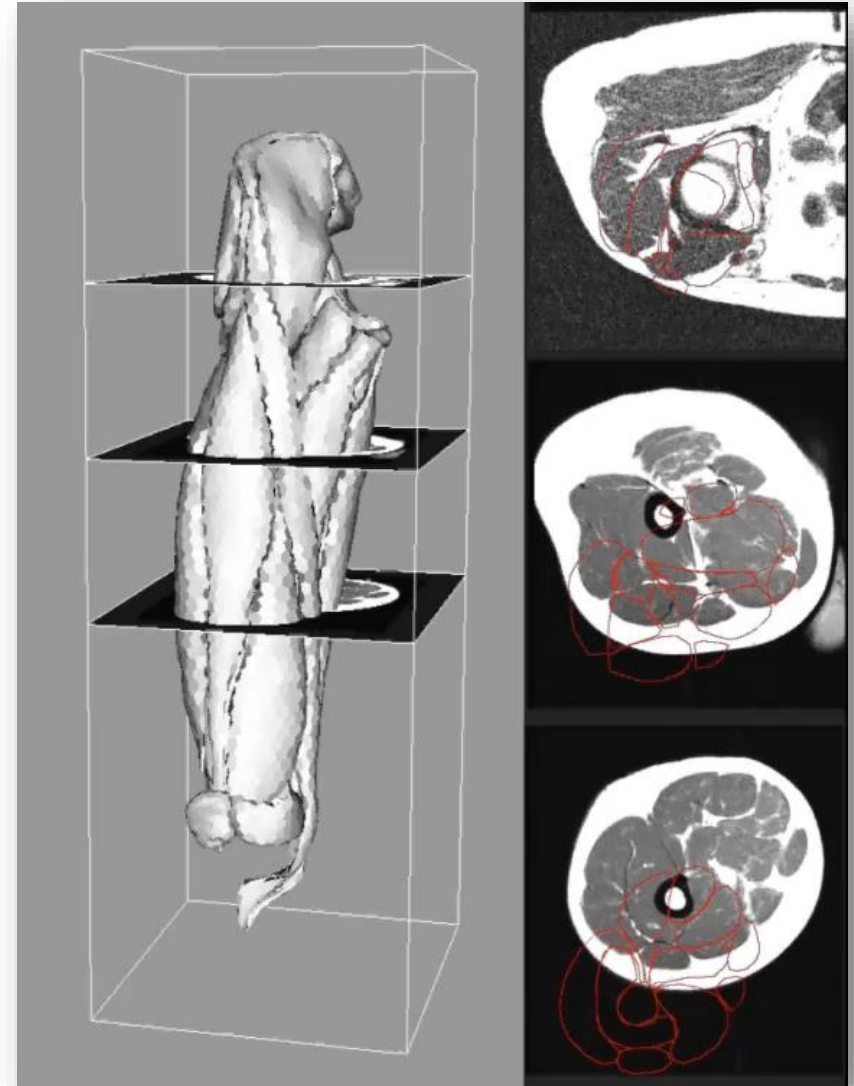


- **Assess the result in the 3D image.**
- **If not, take the model of another anatomical structure.**



# Conclusions

- ❑ Deformable models can be used for segmentation in **many applications** in 3D imaging (e.g. segmentation of thigh muscles in MR images);
- ❑ May give good results if the **shape is smooth or can be characterized**;
- ❑ Very interested **to collaborate** on this topic (palaeoanthropology, medicine, geology... ?);
- ❑ Some software is **freely available** for testing in specific applications ( <http://www.lsis.org/endex/> ).



*B. Gilles, L. Revéret, D.K. Pai. "Creating and animating subject-specific anatomical models", Computer Graphics Forum, 29(8), pp 2340-2351, 2010.*

**Thank you for your attention.**