

# Morphological analysis on structural MRI for the early diagnosis of neurodegenerative diseases

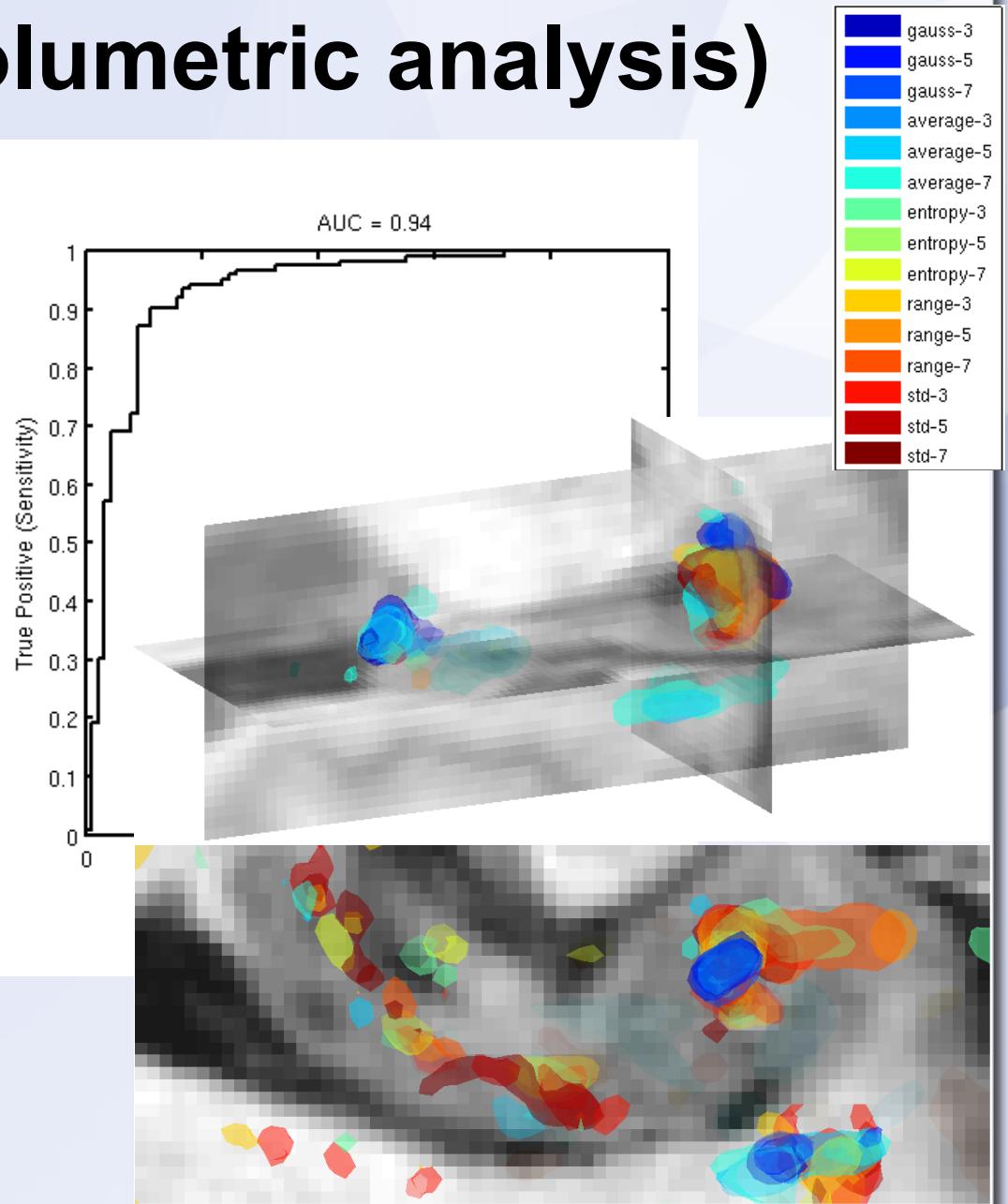
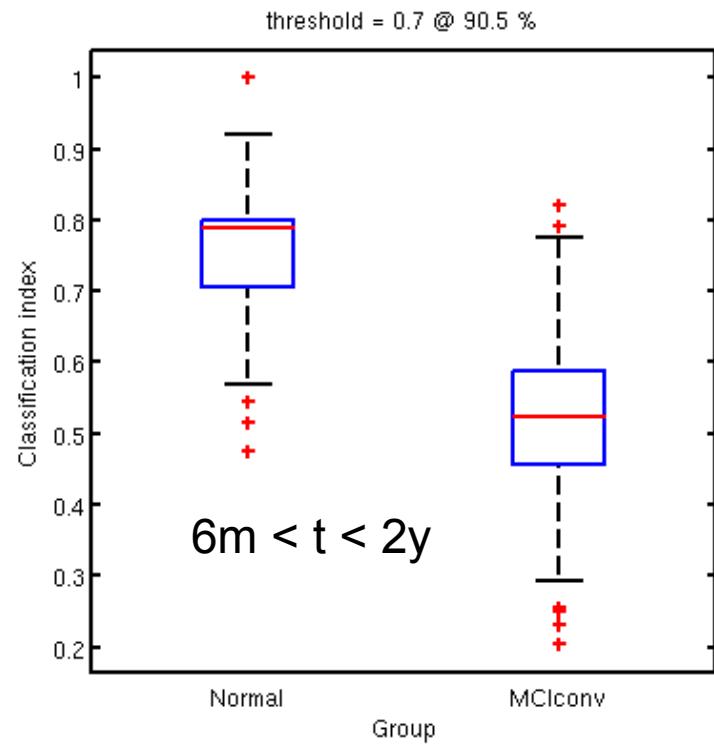
Marco Aiello

On behalf of MAGIC-5 collaboration

# Index

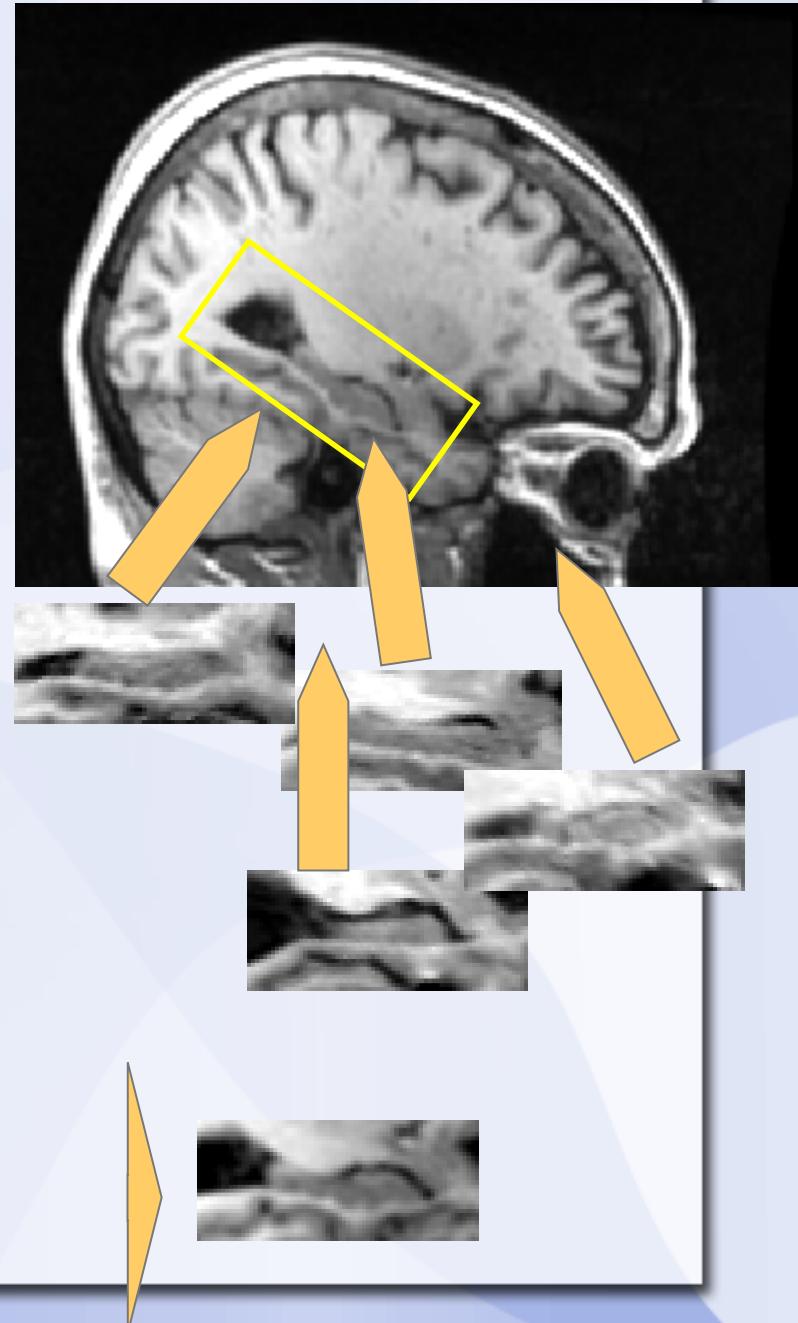
- Motivations of morphological analysis
- Segmentation of hippocampal region
- Template-based segmentation
- Voxel-based segmentation
- Shape analysis
- Conclusions and future works

# Key result (volumetric analysis)



# Segmentation

- From the boxes generated such as the volumetric analysis, we want to find the hippocampal structure

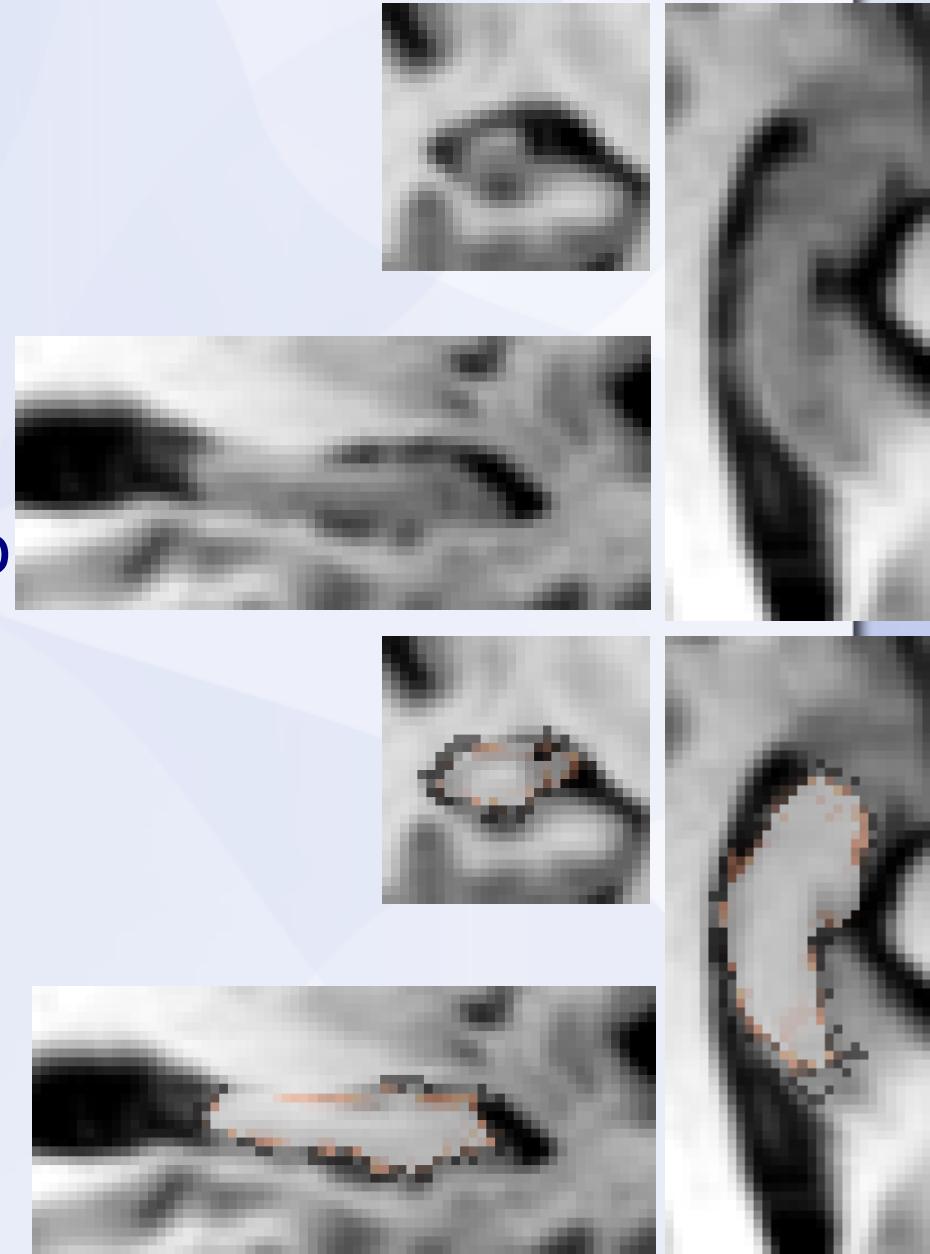


# Segmentation goal

- Retrieve automatically the hippocampus shape

## Difficulties:

- Gray matter structure near to some gray matter structures
- Low contrast and no well-defined contours

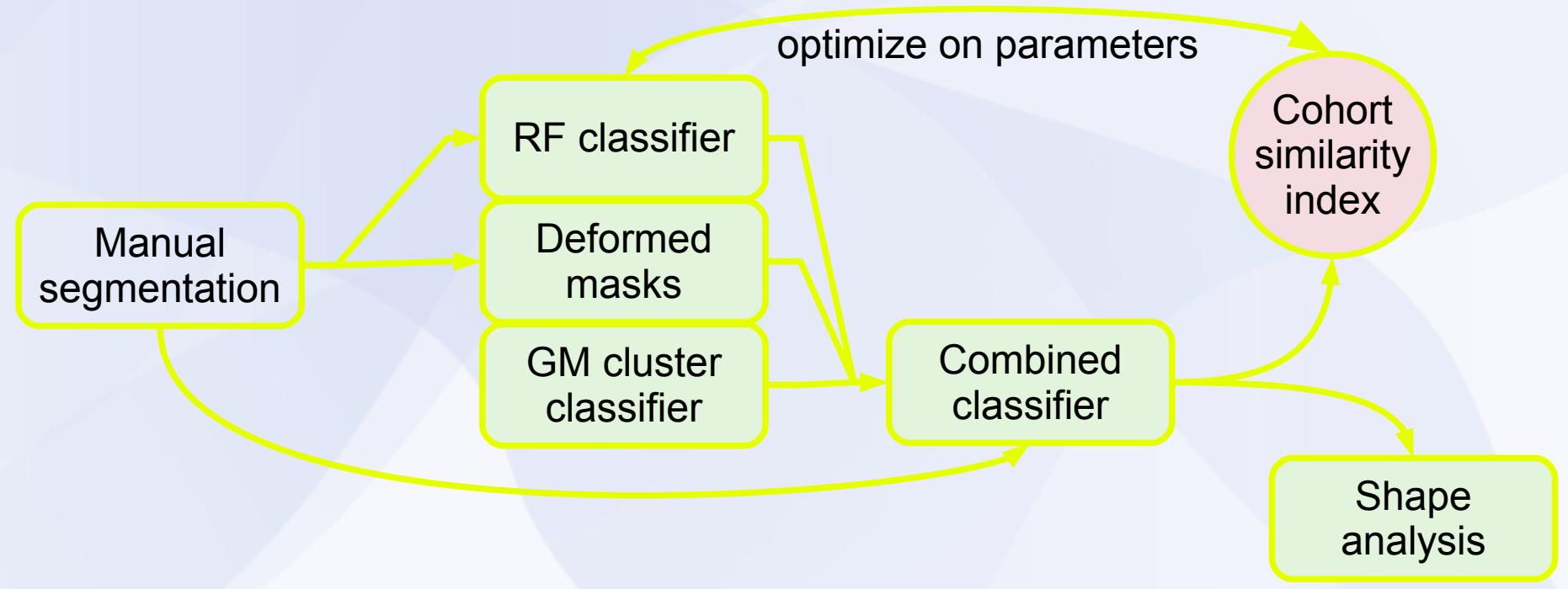


# Segmentation methods

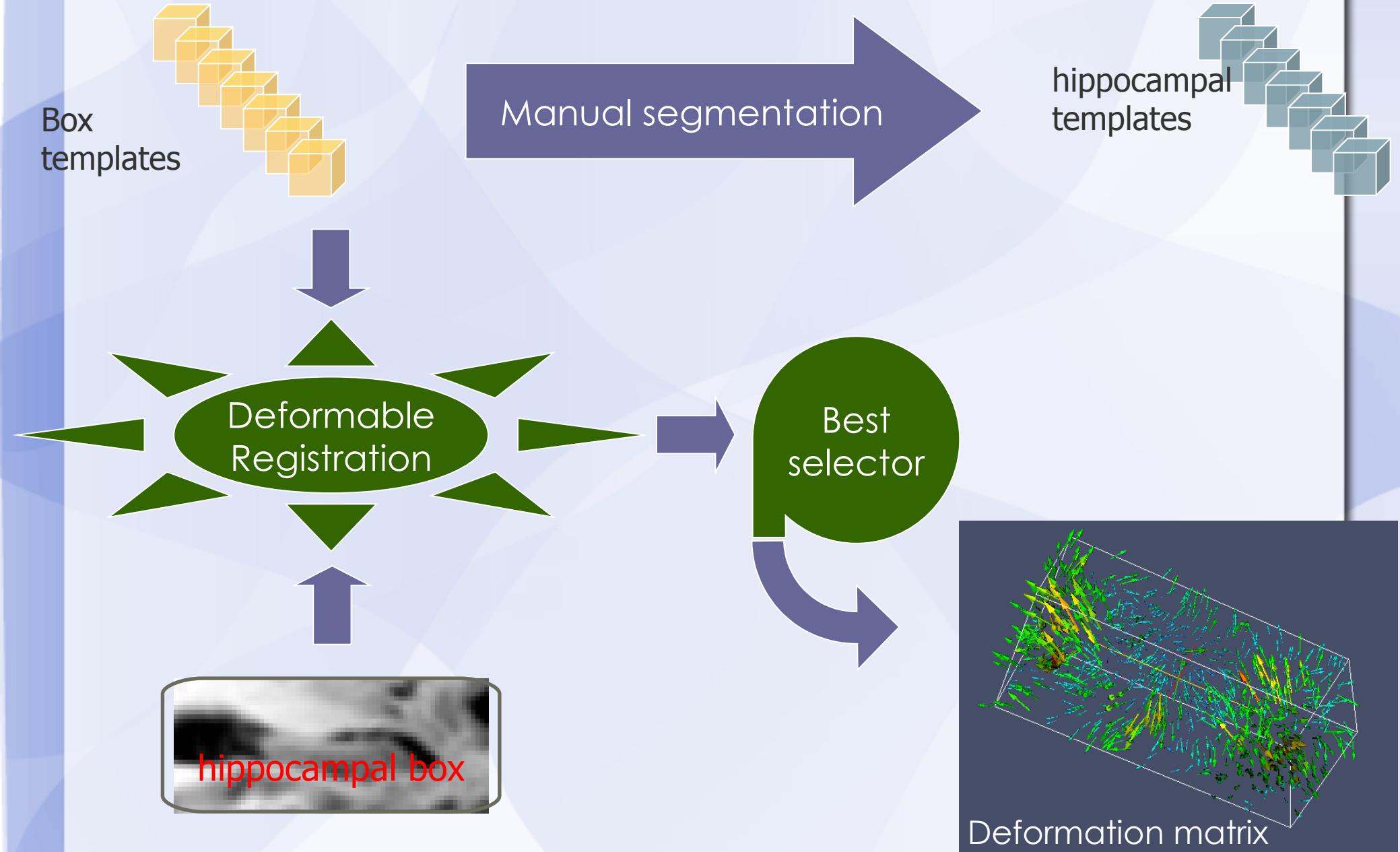
- Snakes, Watershade, Region Growing...
- Voxel-based approach (Clustering and supervised classification)
- Template-based approach (deformable masks)

# Our Segmentation approach

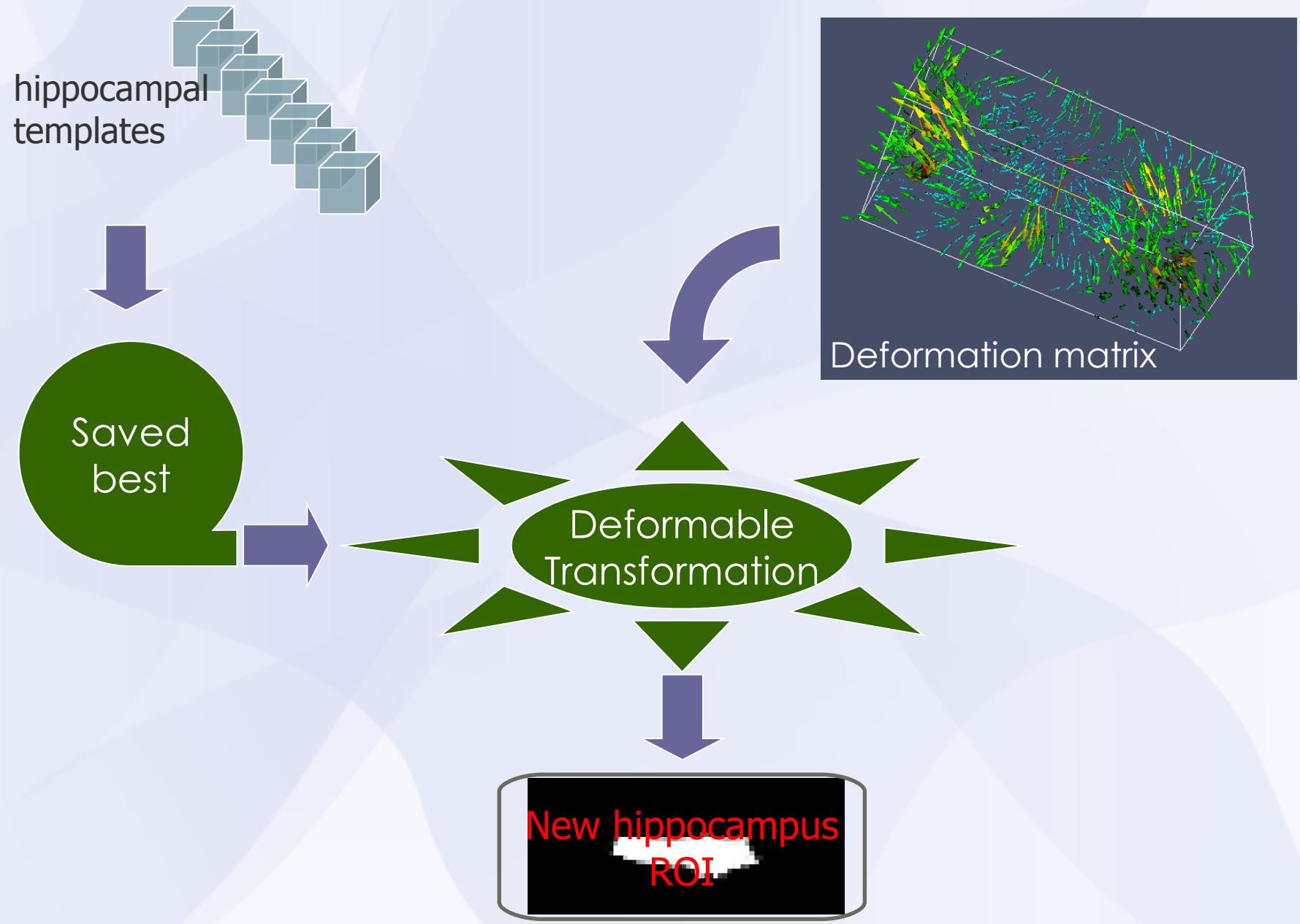
- Integration of multiple segmentation methods
- Shape consistency check (similarity index)
- Multiple approach path



# Deformable masks



# Deformable masks (2)



# Deformable Registration

- Physical continuum model, viscous fluid mechanics (Thirion's algorithm)
  - In this scheme each image is viewed as a set of iso-intensity contours
  - The main idea is that a regular grid of forces deform an image by pushing the contours in the normal direction
  - The orientation and magnitude of the displacement is derived from the instantaneous optical flow equation
- Maintains topology and connectivity of deforming template

$$D(x) \cdot \nabla f(x) = - (m(x) - f(x))$$

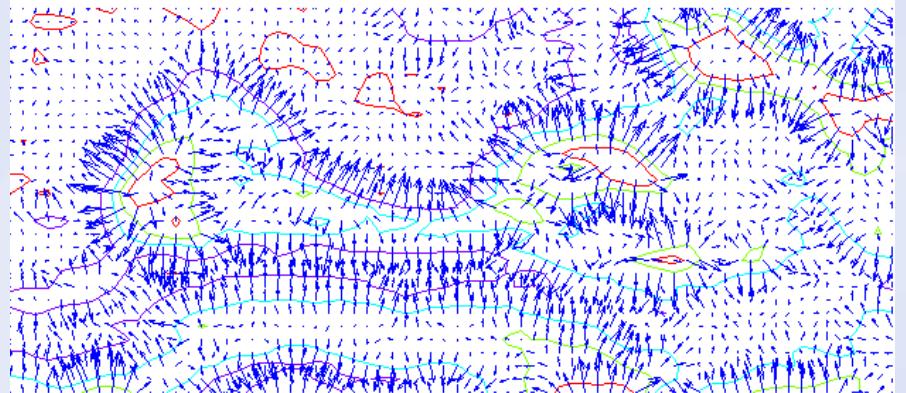
# Warping

Mean square metric

$$MS(A, B) = \frac{1}{N} \sum_{i=1}^N (A_i - B_i)^2$$

Voxel of the moving image

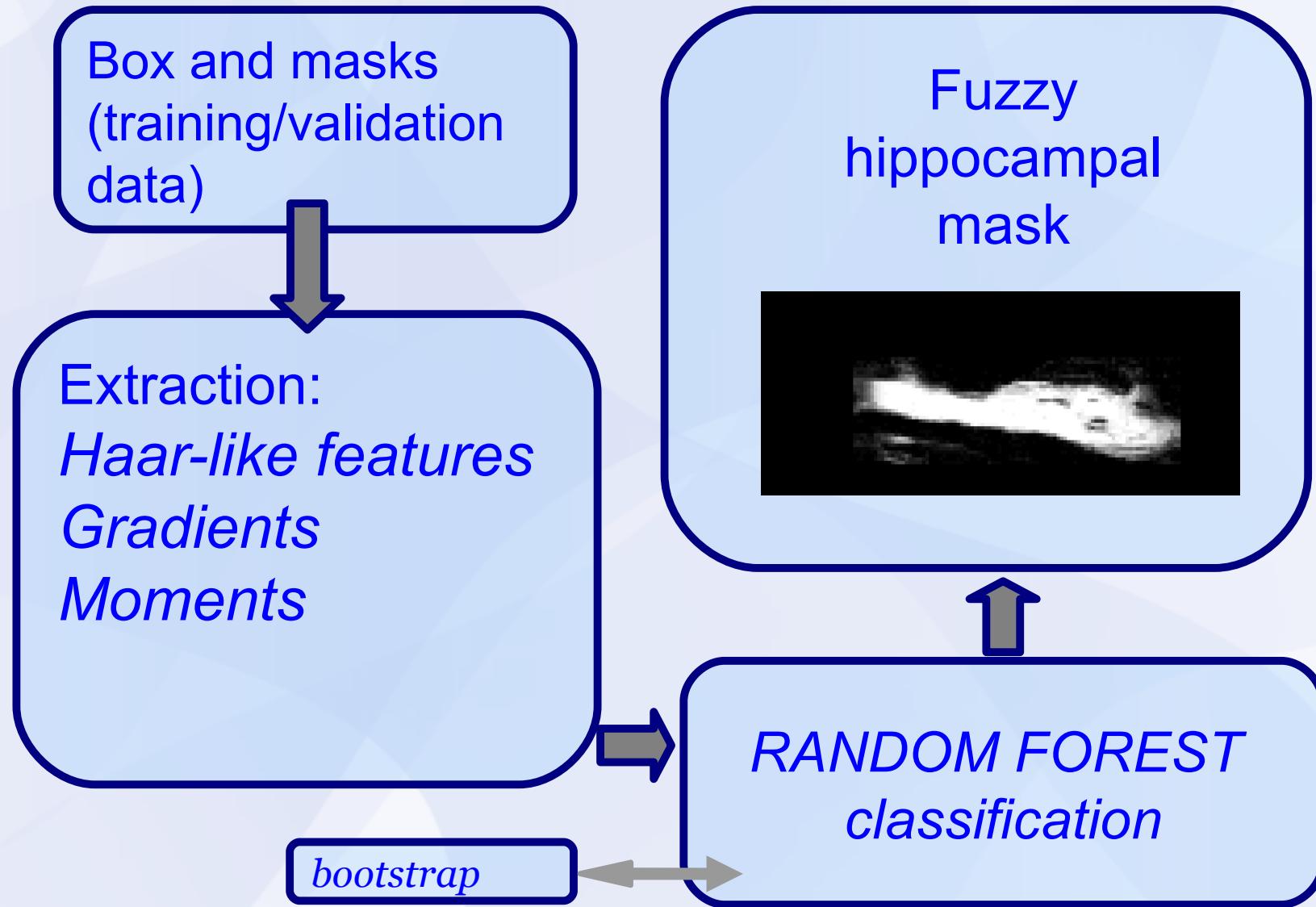
Voxel of the fixed image



$$D(x) \cdot \nabla f(x) = - (m(x) - f(x))$$

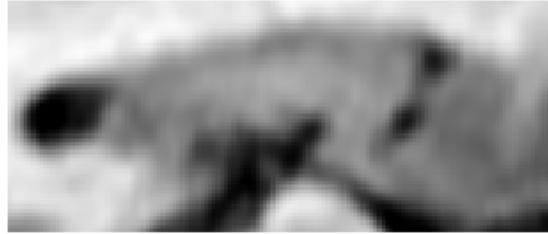
- Simple to compute
- Large capture range
- Restricted to mono-modality applications
- Linear differences in intensity results in poor similarity measure
- We need that *similar gray values correspond to similar tissues!* histogram normalization is required!

# Supervised classification

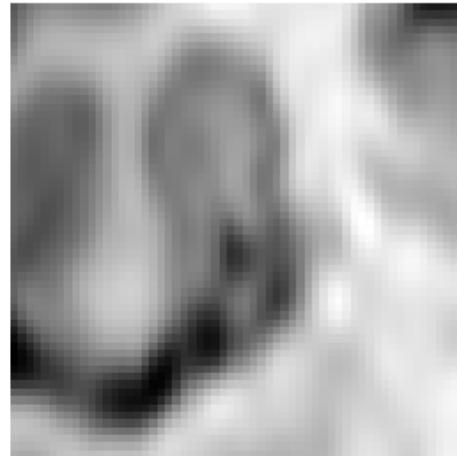


# Training set

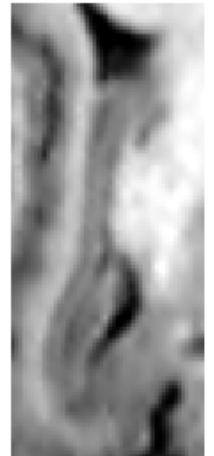
axial real slice n. 30



coronal real slice n. 80



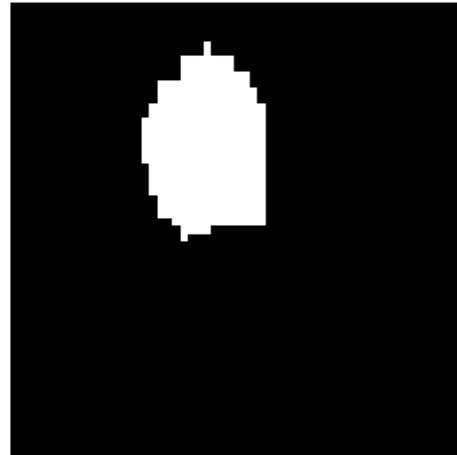
sagittal real slice n. 30



axial mask slice n. 30



coronal mask slice n. 80



sagittal mask slice n. 30

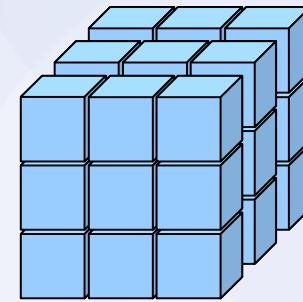
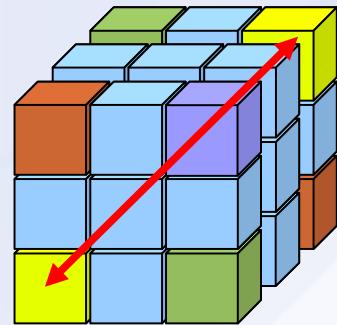


# Features extraction

- 3D texture analysis
- Our features are derived from gradients and first order statistic (*mean, std, skewness, entropy..*)

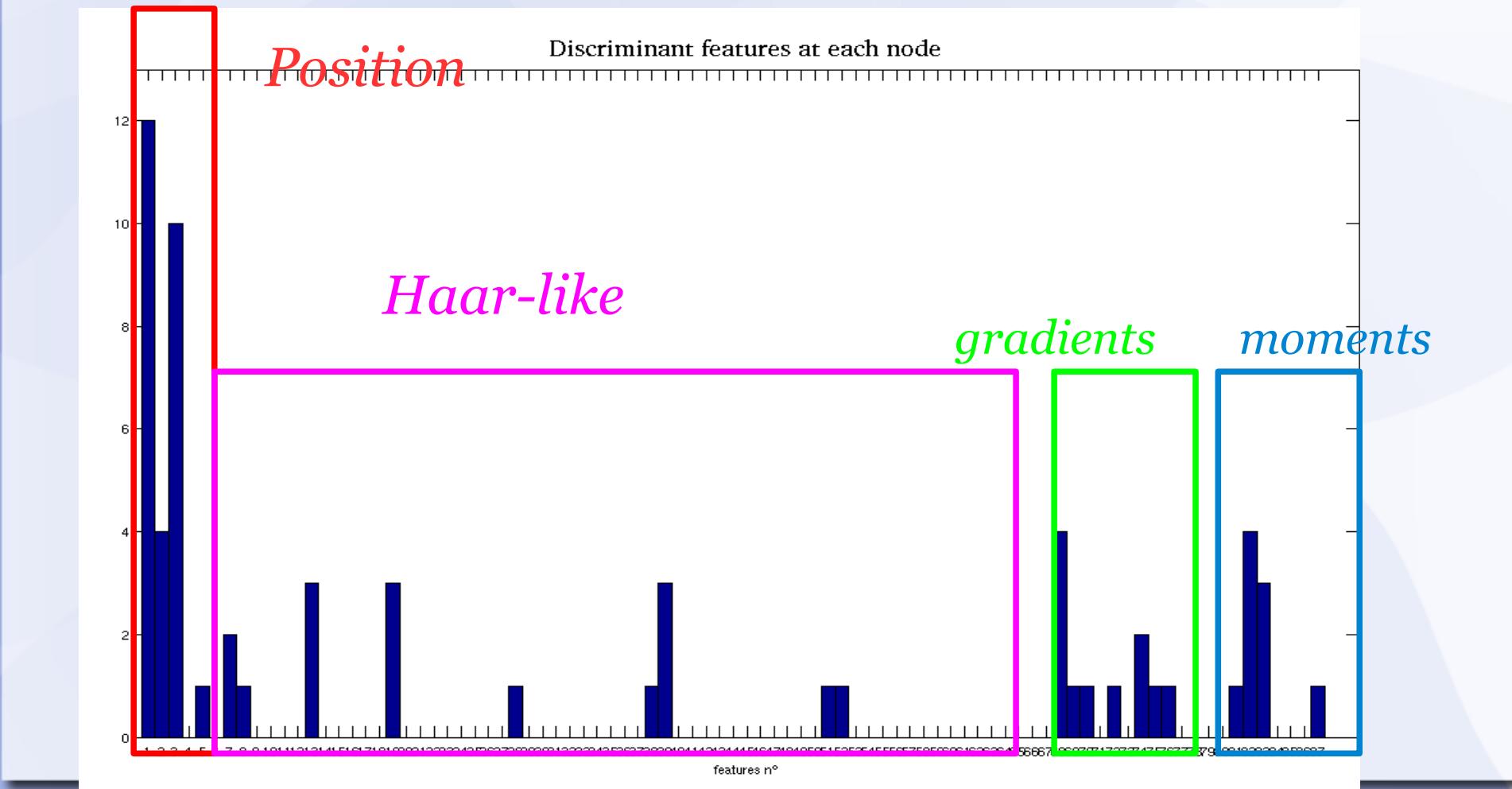
***The haar-like features*** are calculated on masks of different dimensions (3x3x3 up to 9x9x9) centered on the voxel of interest.

We obtain almost ***3000 features for each voxel.***



# Features selection

- Bootstrap for data selection
  - Most relevant features discrimination

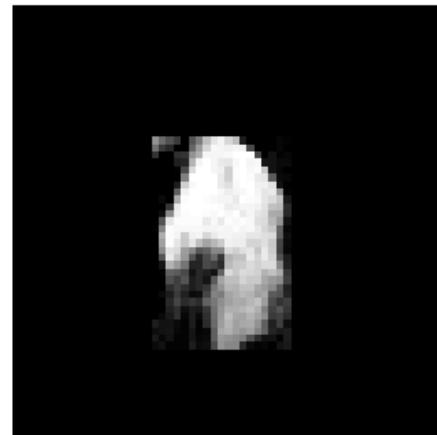


# Results

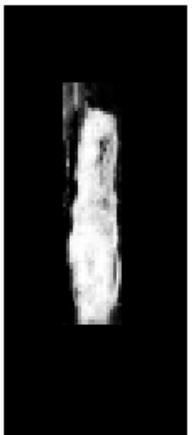
axial RF slice n. 30



coronal RF slice n. 80



sagittal RF slice n. 30



axial mask slice n. 30



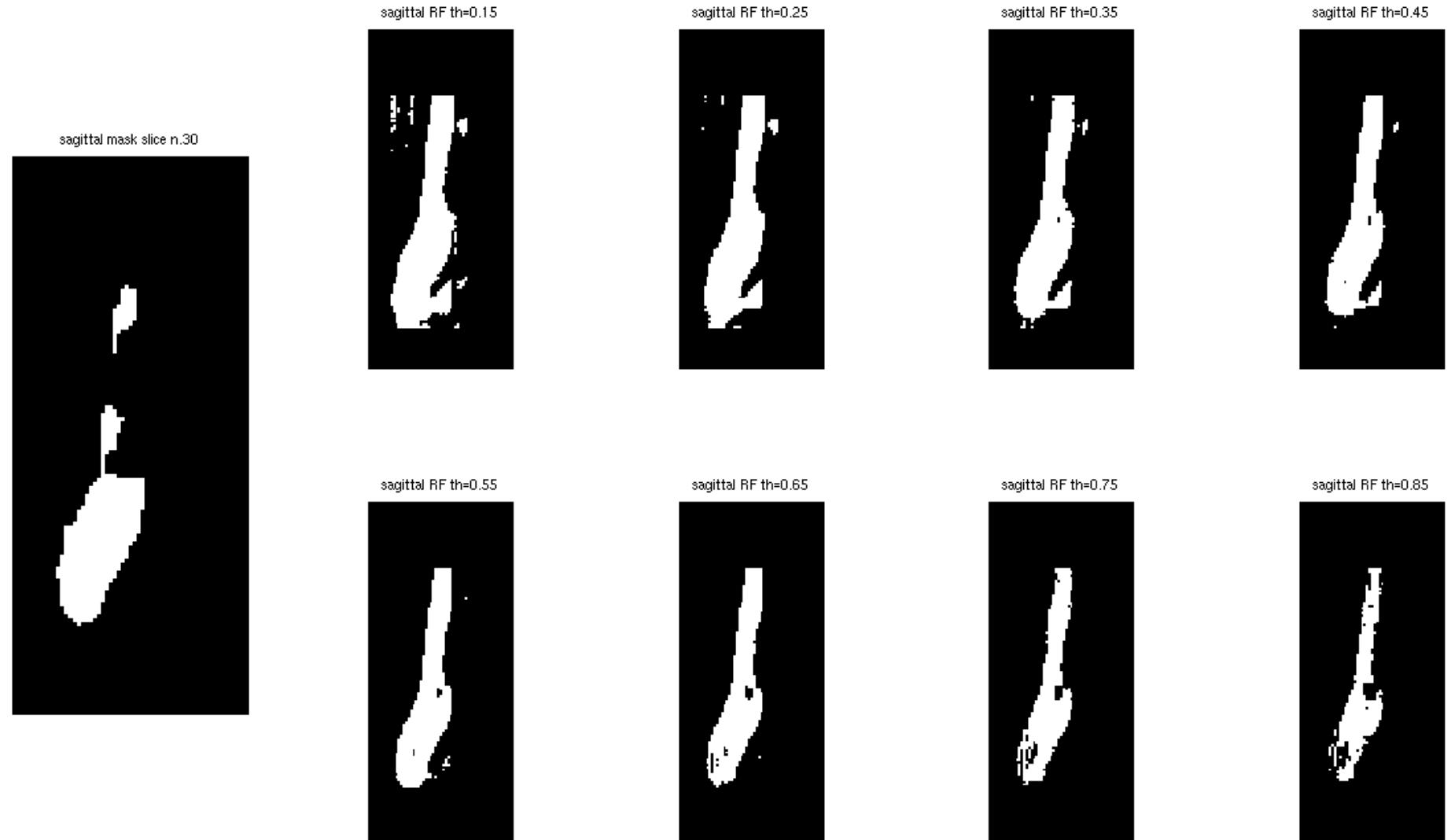
coronal mask slice n. 80



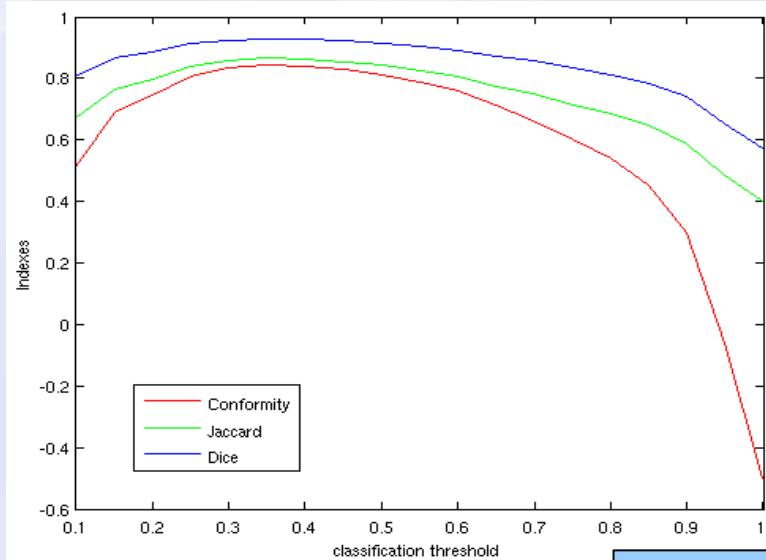
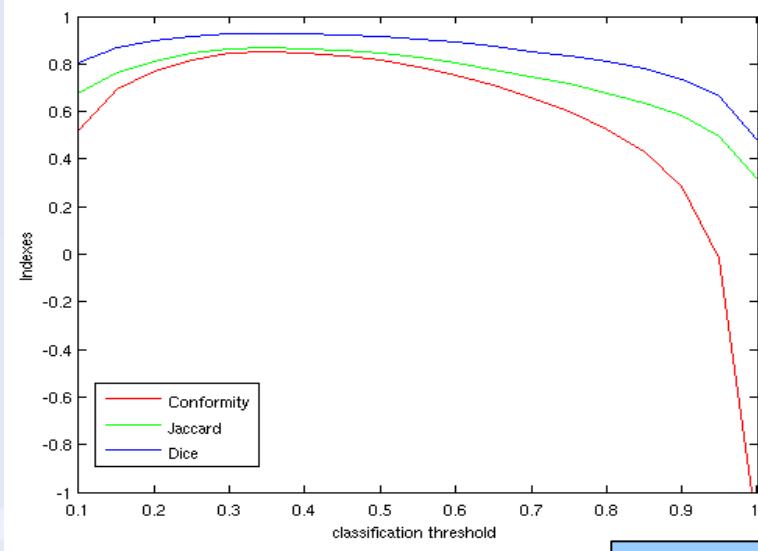
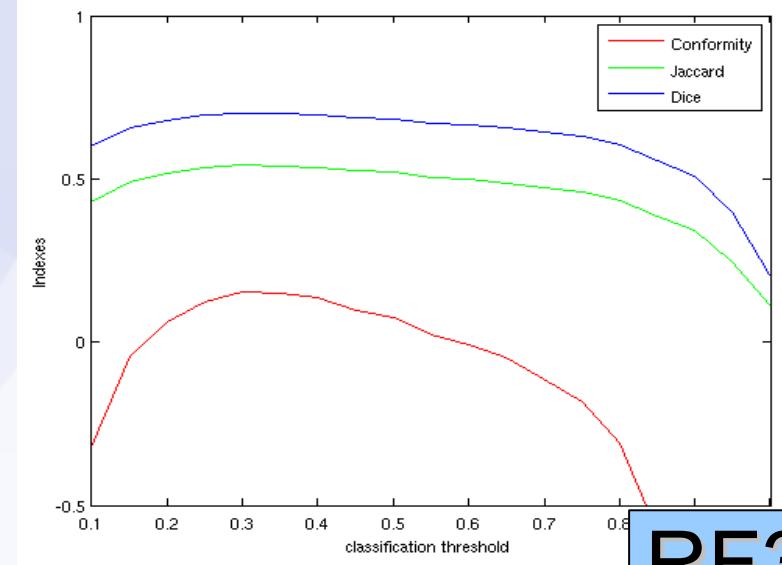
sagittal mask slice n. 30



# Fuzzy hippocampal mask

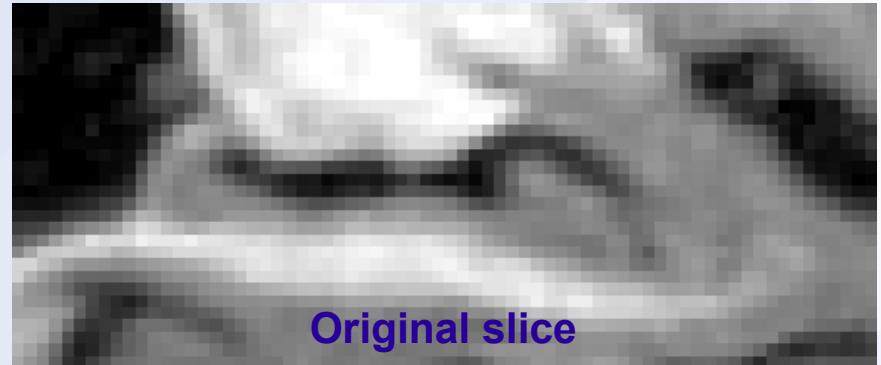


# Results

**RF1****RF2****RF3**

# Unsupervised classification (k-means)

- 3-classes (GM,WM,CSF) intensity-based clustering
- Rough segmentation
- PVE correction by erosion/dilation



Original slice

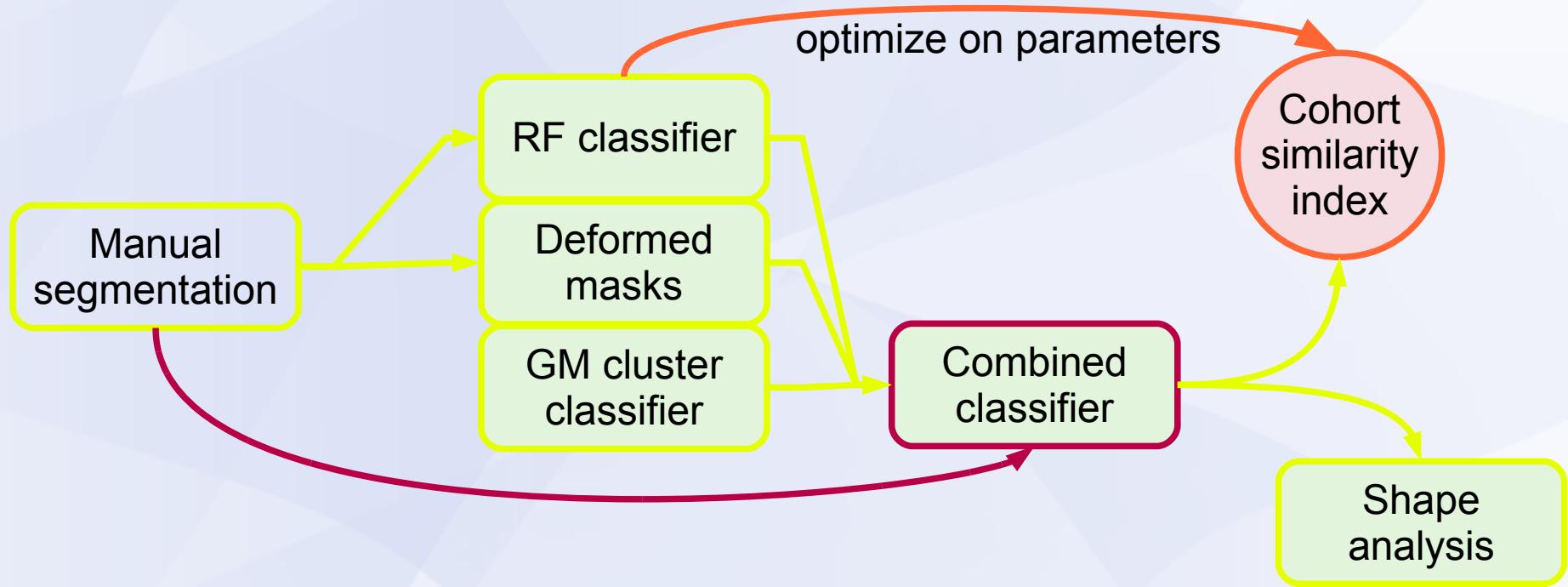


GM class



PVE correction

# Pipeline reminder



# Combined classifier

- We have different hippocampal masks derived from different segmentation methods
- We want to combine this information into a single meaningful mask
- STAPLE (Simultaneous Truth and Performance Level Estimation)
- Algorithm for the performance estimation of raters when no ground truth exists.

EM instance:

The raters segmentation is observable.

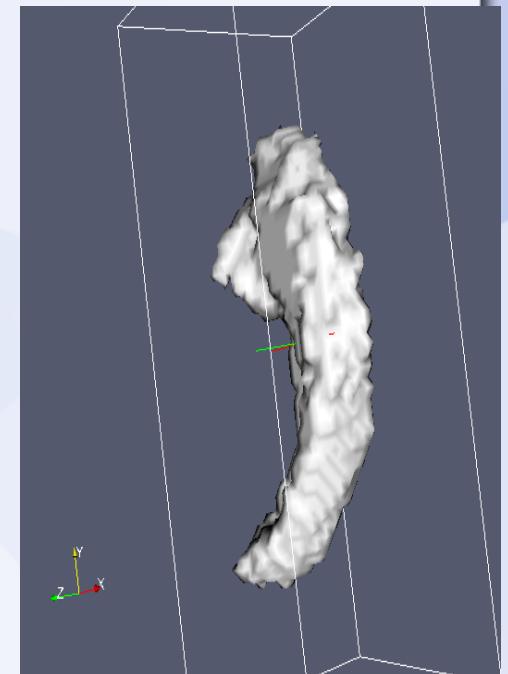
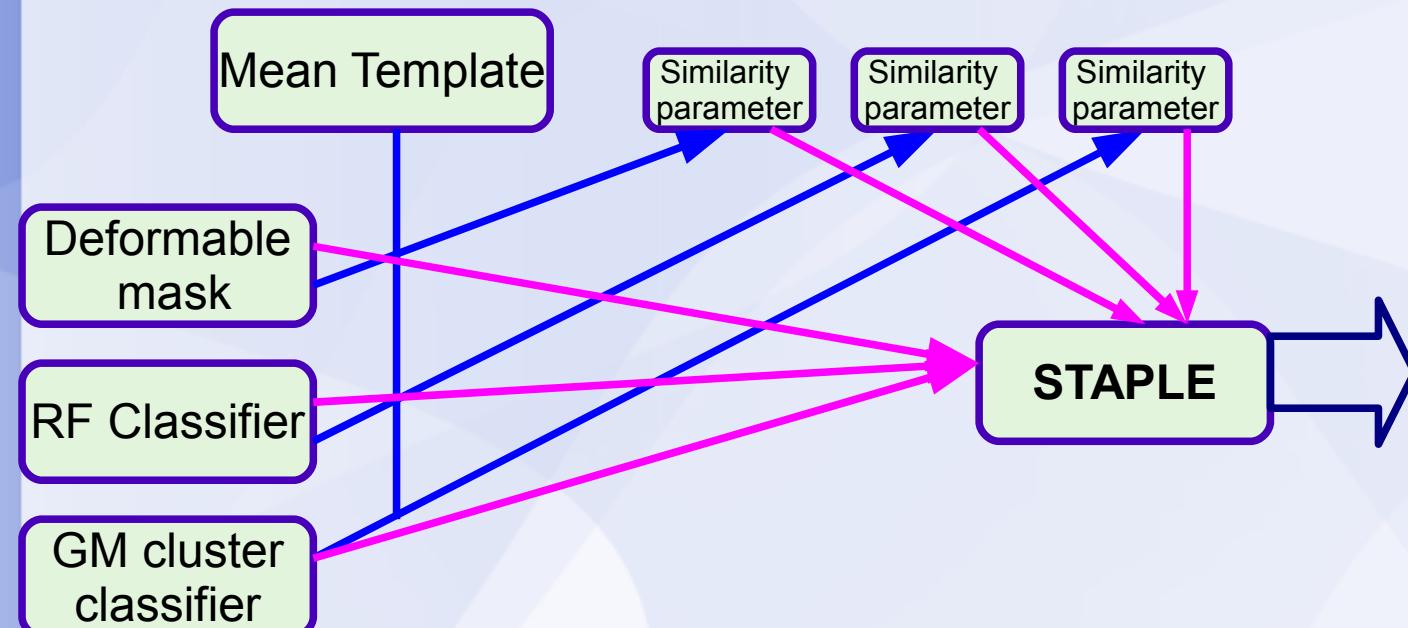
The true segmentation is a "hidden" binary variable

The raters performance level is defined by:

Sensibility  $p$  : true positives rate.  
Specificity  $q$  : true negatives rate.

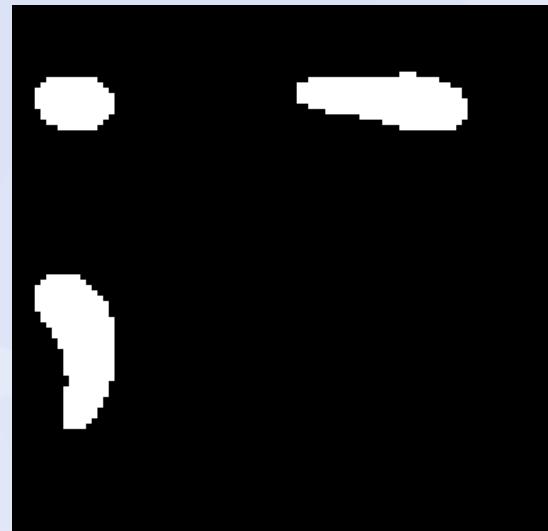
# STAPLE (parameters)

- STAPLEs starting parameters to weigh the raters segmentation



# Consistency check

- Unambiguous hippocampi are similar to template masks



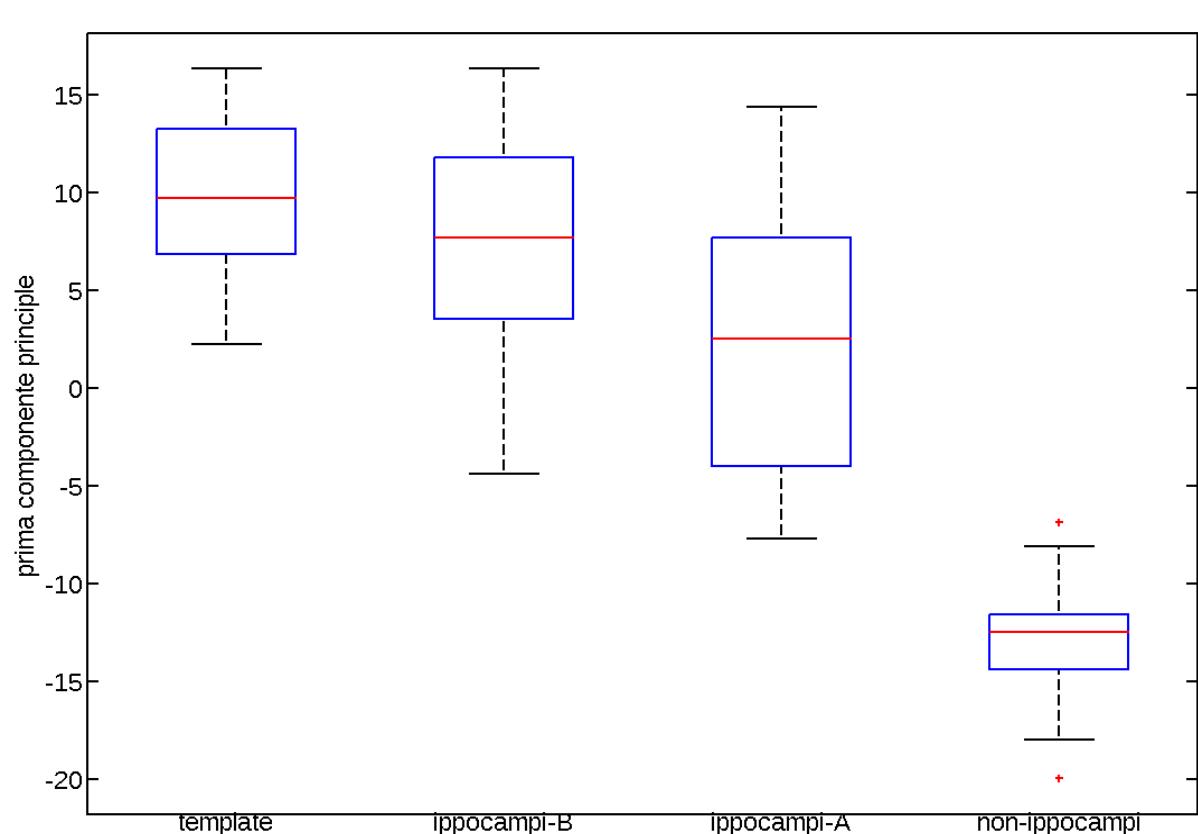
Ippocampo ambiguo



Ippocampo non ambiguo

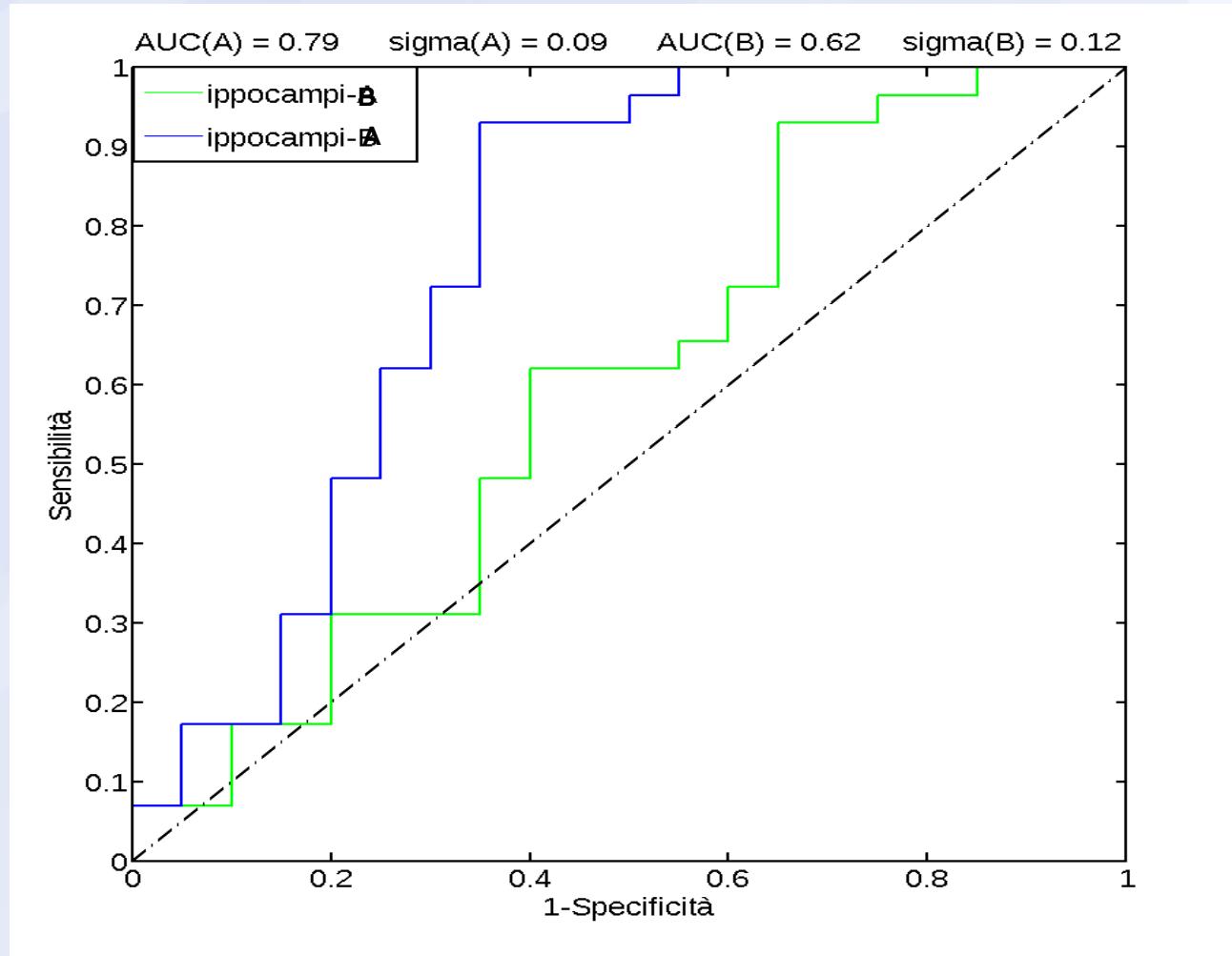
# Consistency check (2)

- Two sets of results: hippocampi-A and hippocampi-B
- PCA-based comparison between *h-A*, *h-B*, *templates* and *non-hippocampi*



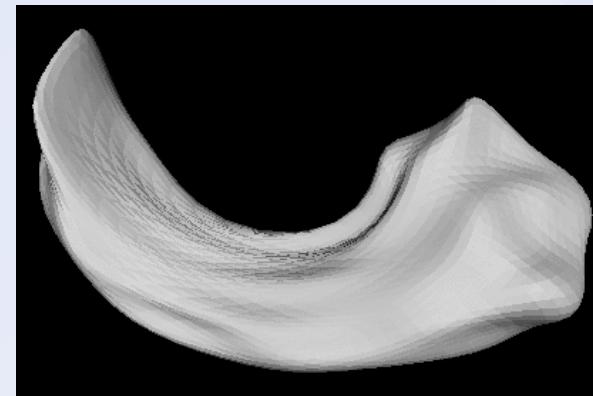
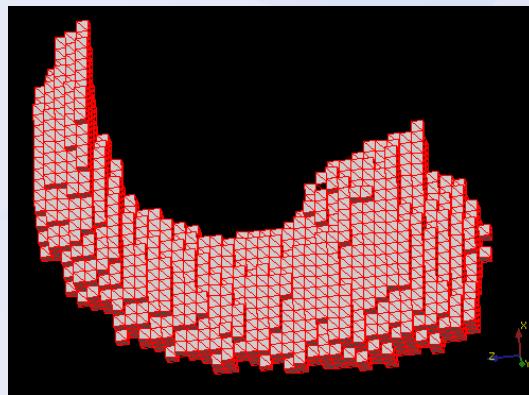
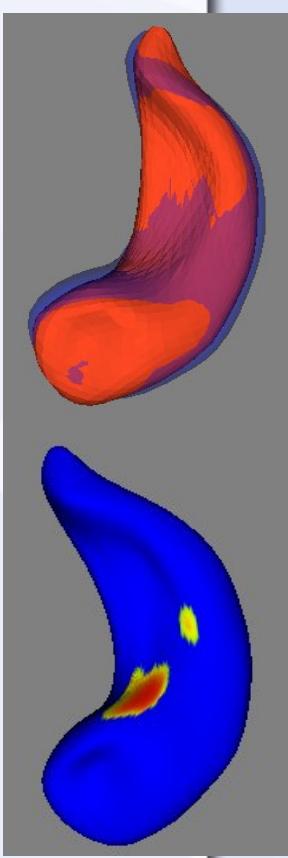
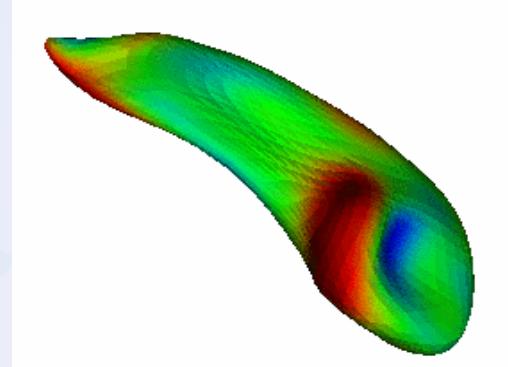
# Consistency check (3)

- Comparison with templates family



# Shape analysis

- Hippocampus shape should be analyzed to find atrophy characteristics
  - Possible method: spherical harmonics analysis using *SPHARM*
  - Metric analysis (diffeomorphism...)
  - All this methods discover the global variability of the shape....SPARSE PCA can measure local variability such atrophy

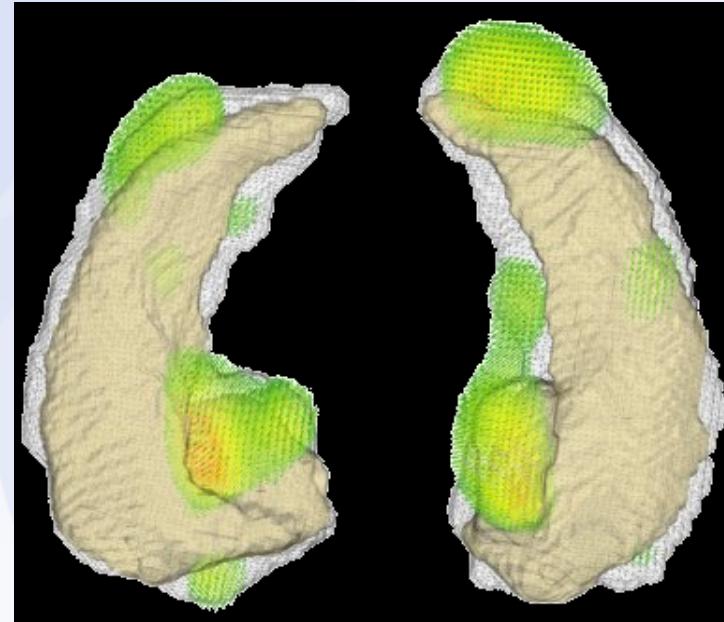


# Sparsity

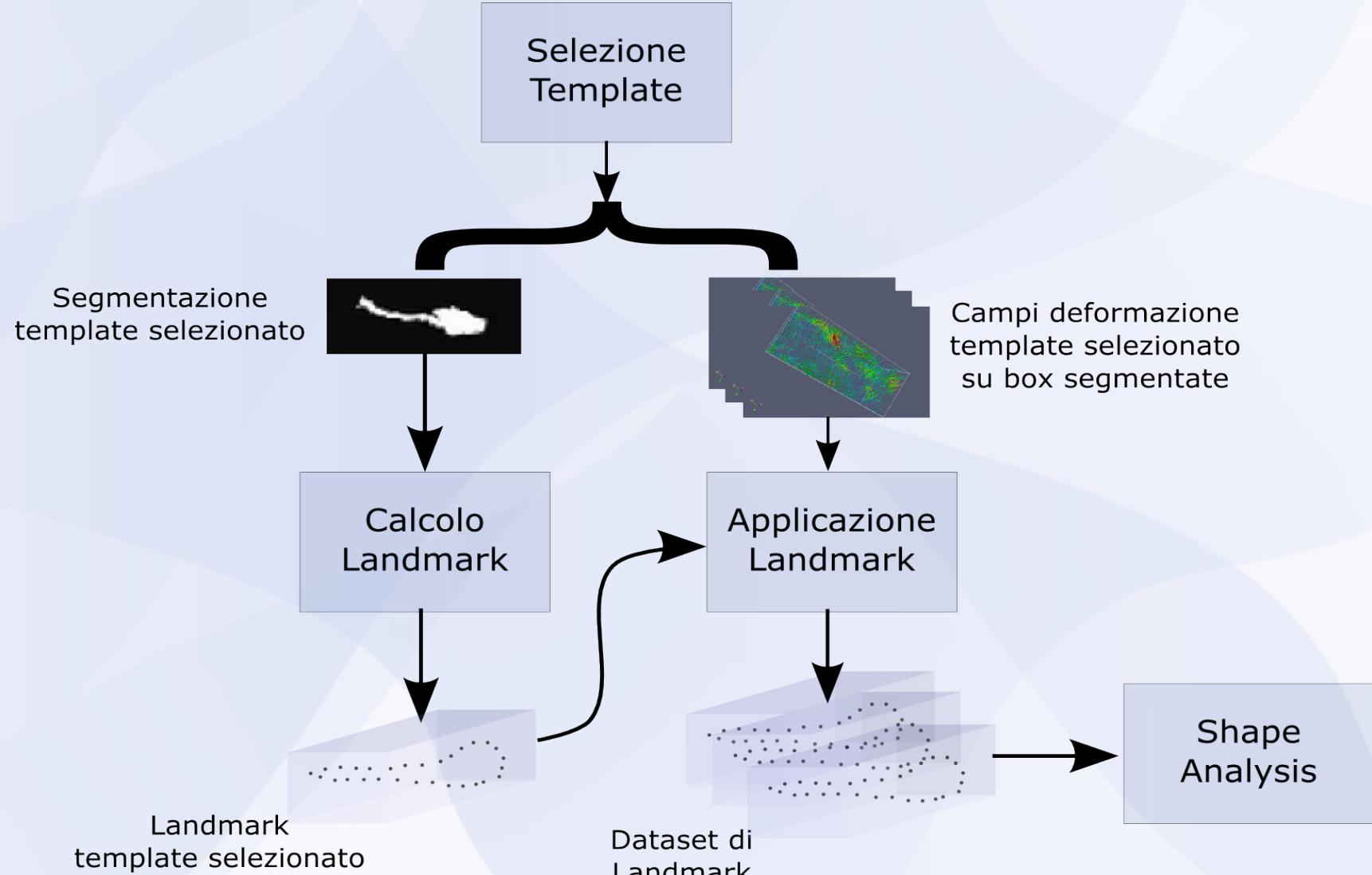
- Sparsity constrains to find localized spatial variability

Null components in the vector of the model parameters  
*(feature selection)*

- Statistical correlation between variables

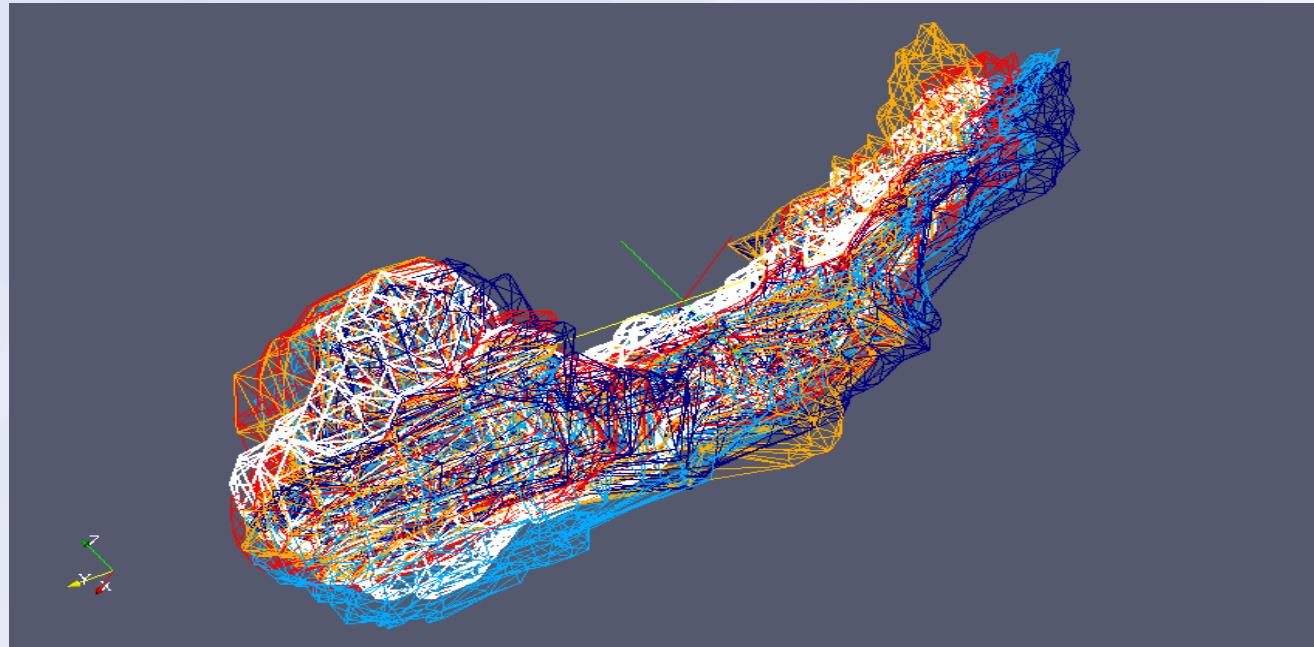


# Sparse PCA

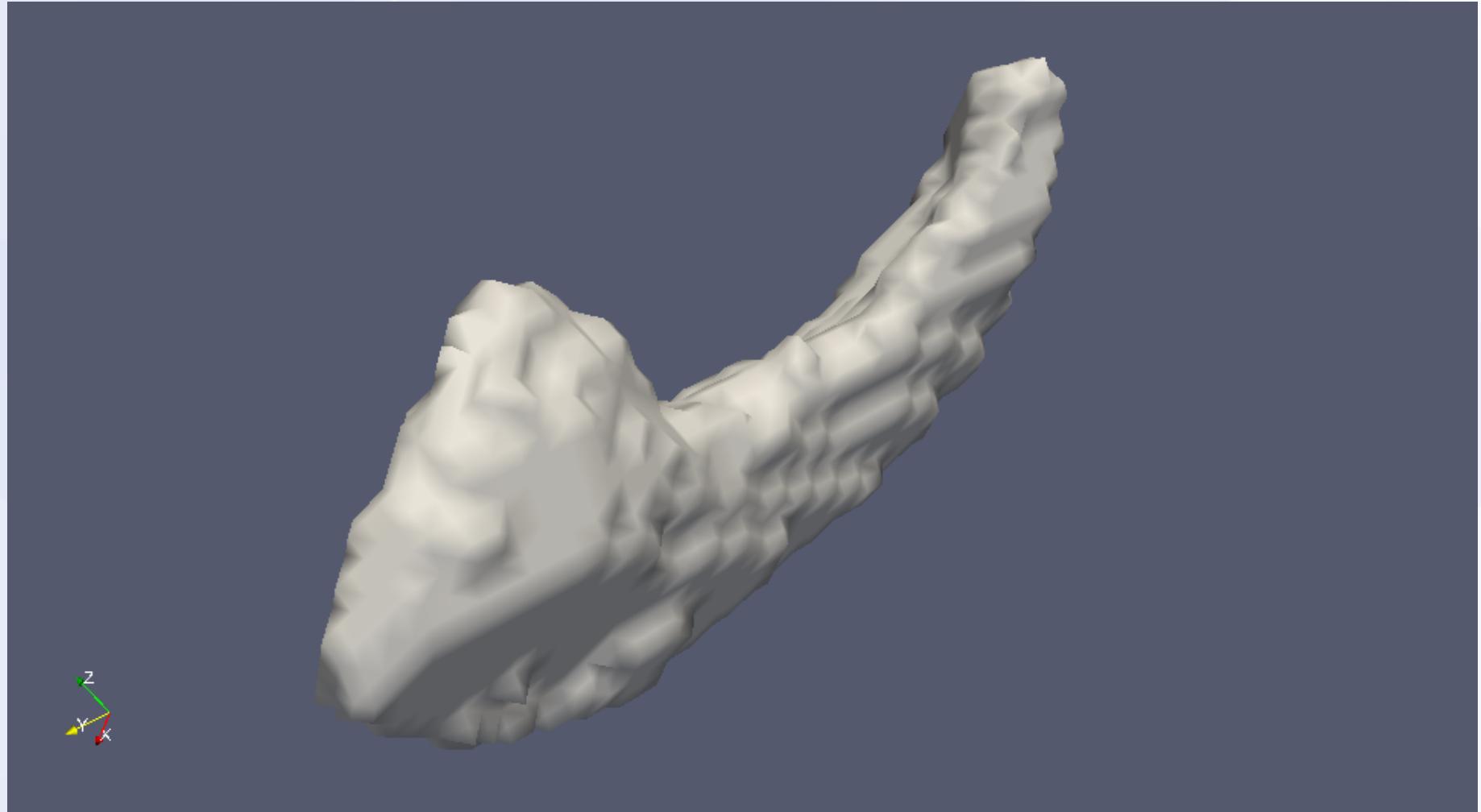


# Dataset

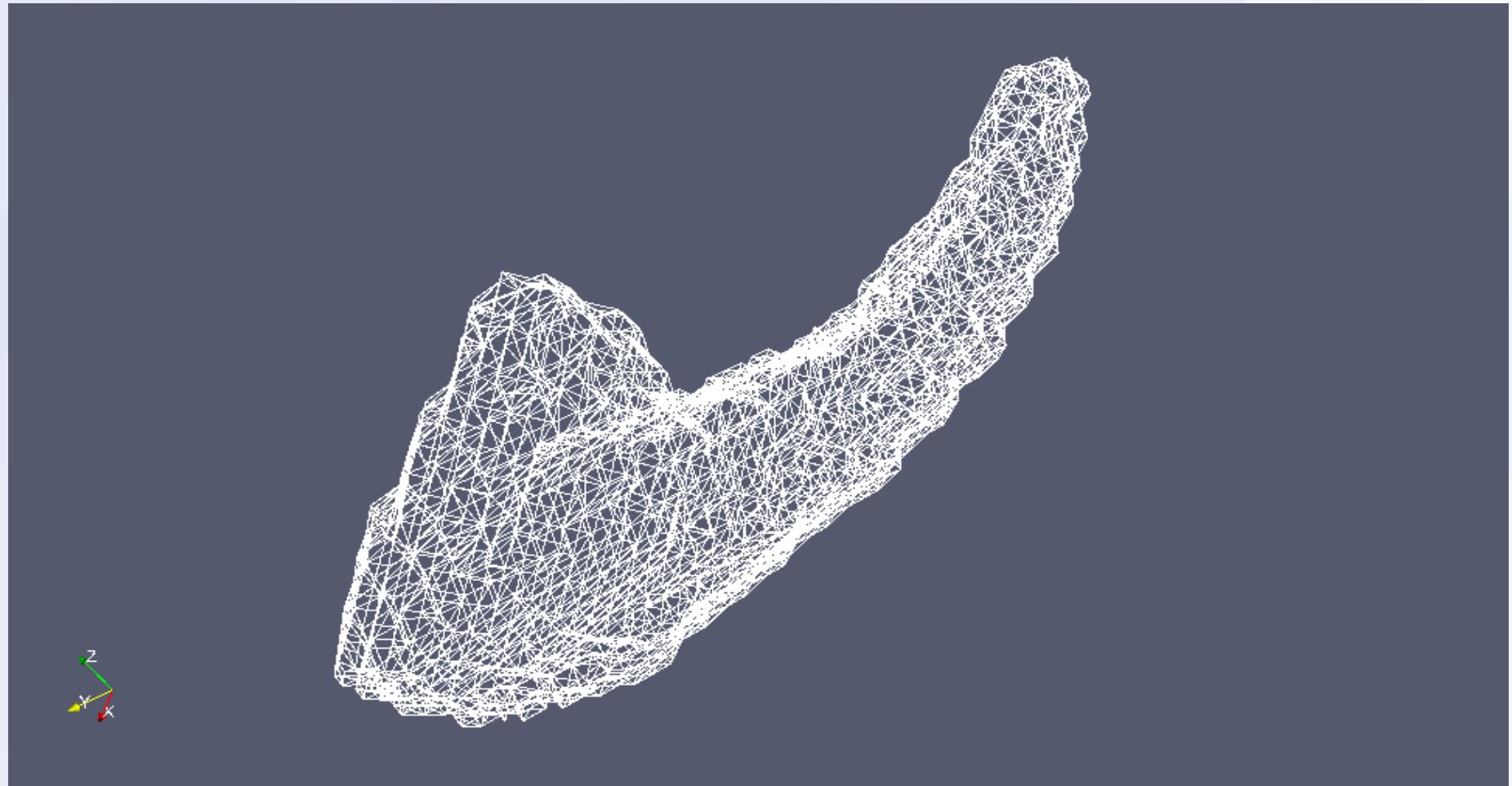
- Mesh on template (2348 landmark)
- Mesh decimation (1644 landmark)
- Deformation fields selection
- Warping of the template on reference hippocampus



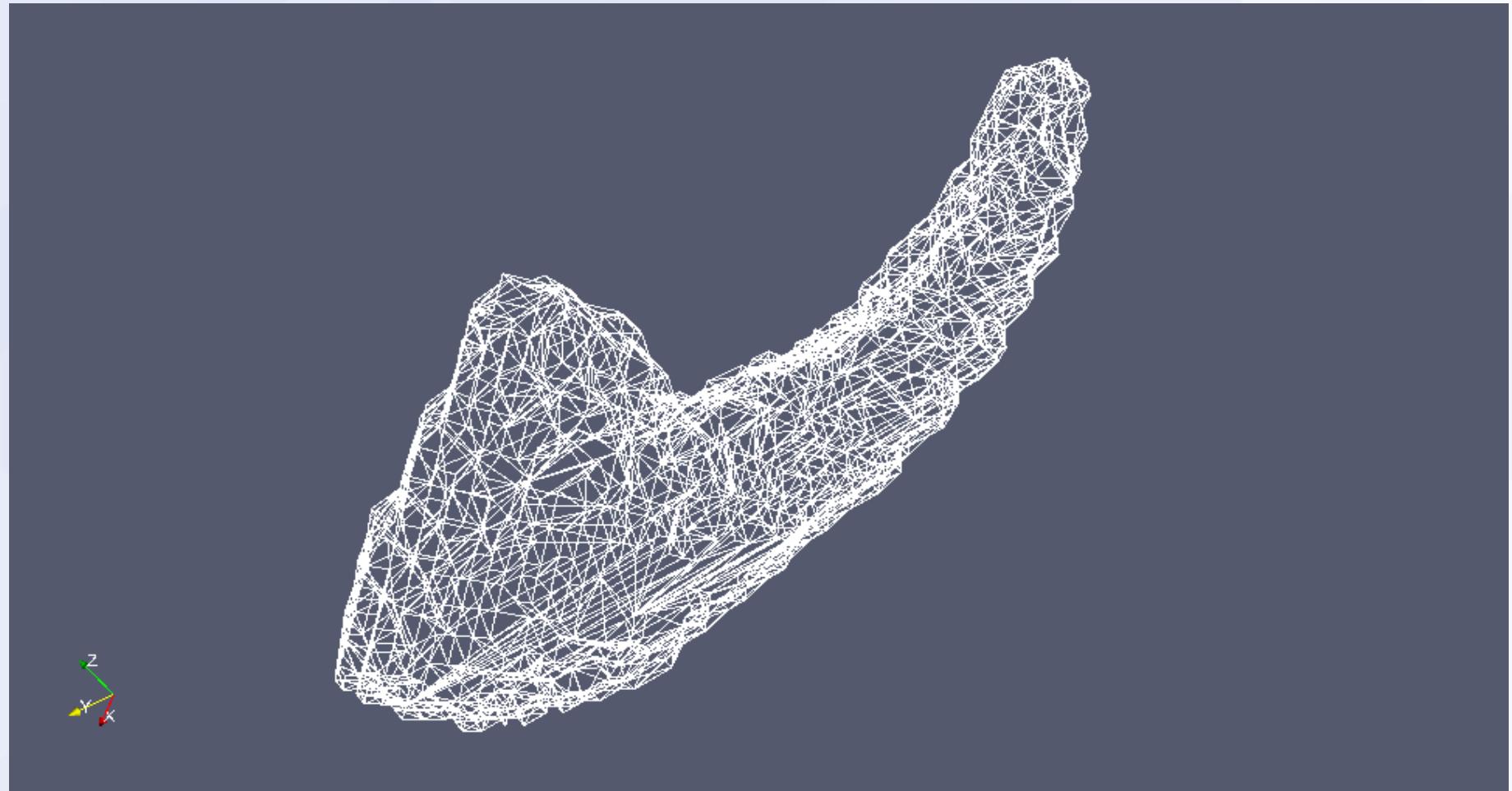
# Reference hippocampus



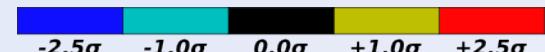
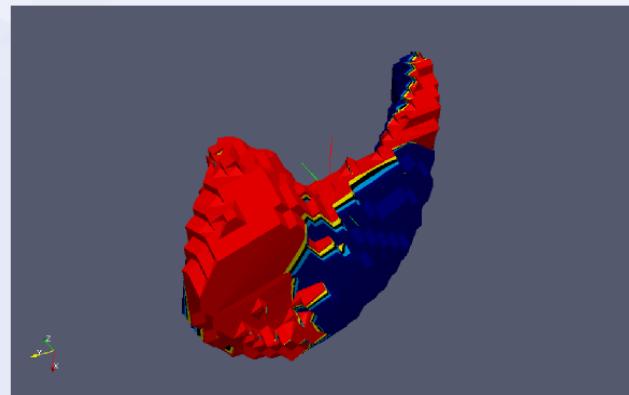
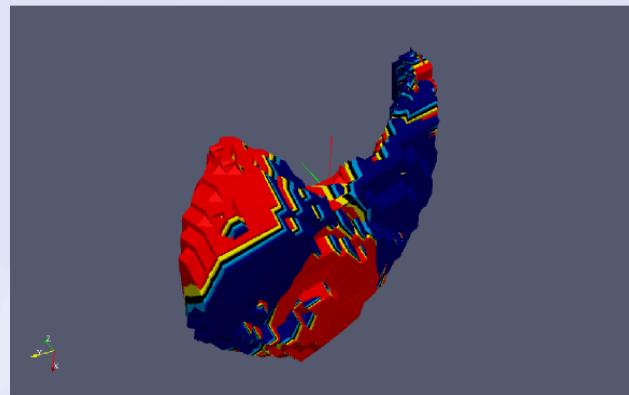
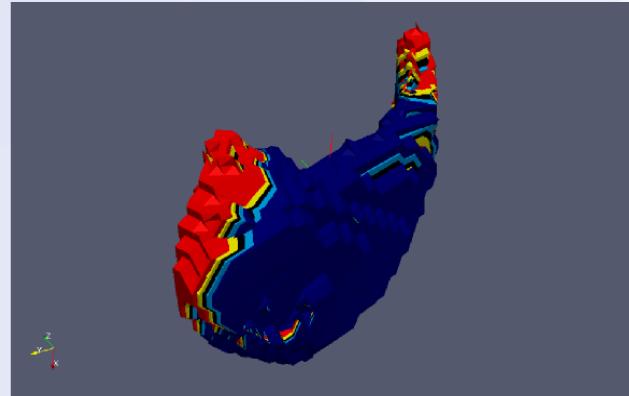
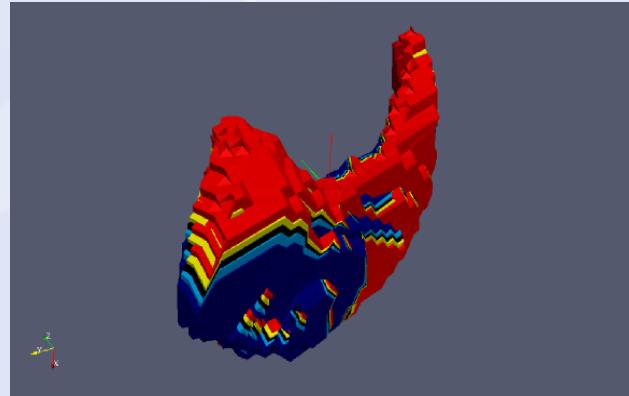
# Reference mesh (2348 landmark)



# Decimated mesh (1644 landmark)



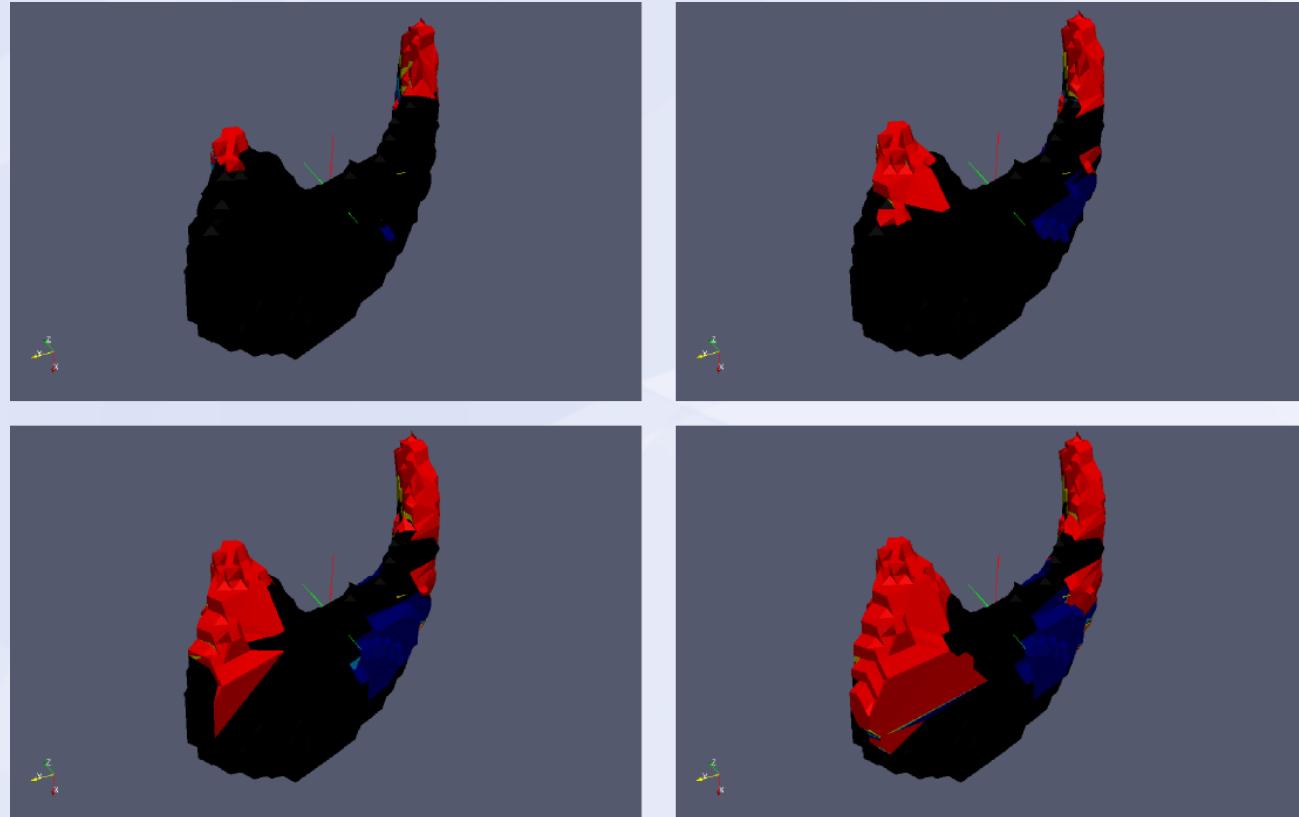
# Principal component analysis (PCA)



95 segmentations dataset

1644 3D landmarks (4932 variables) for each shape

# Sparse Principal Component (SPCA)



First principal component  
5% up to 20% of the variables ( 5% step)

# Conclusions and future works

- A **fully automatic** segmentation pipeline of the hippocampal region
- The **integration** of various, complementary approach can provide a finer segmentation
- The **consistency check** improve the robustness of the pipeline
- Our shape analysis can provide a **local variations** information

## In progress:

- Validation: gold standard to evaluate our results (EADC protocol)
- Relation between shape analysis parameters and clinical score

# Thanks!