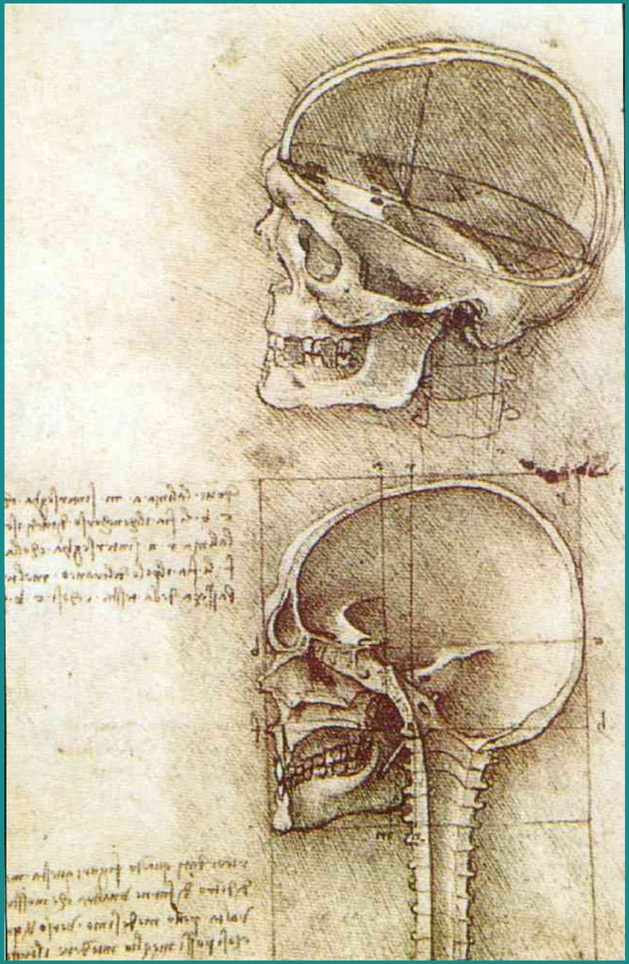
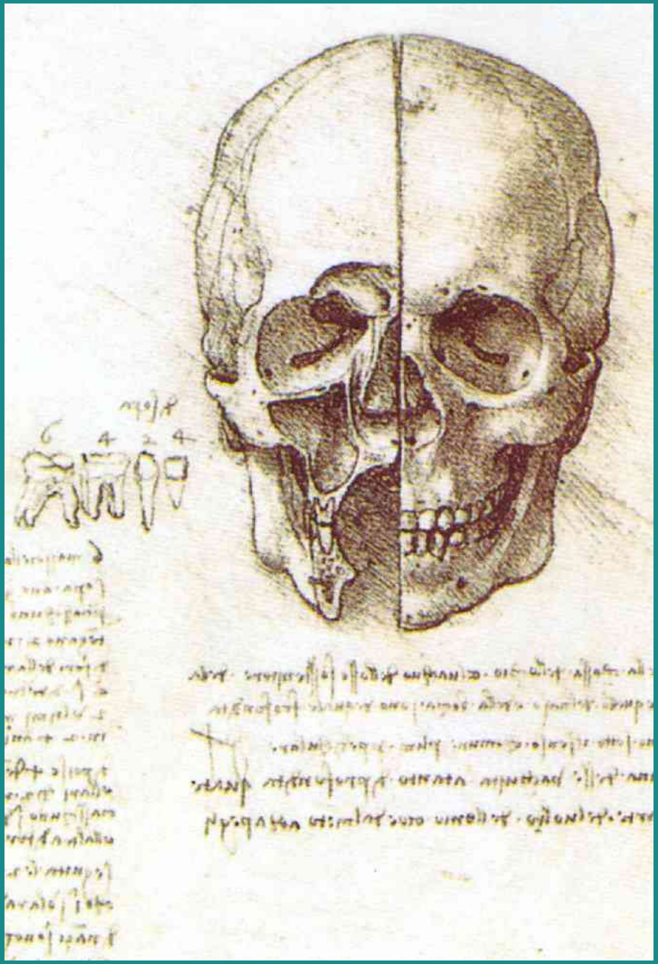
Medical Imaging





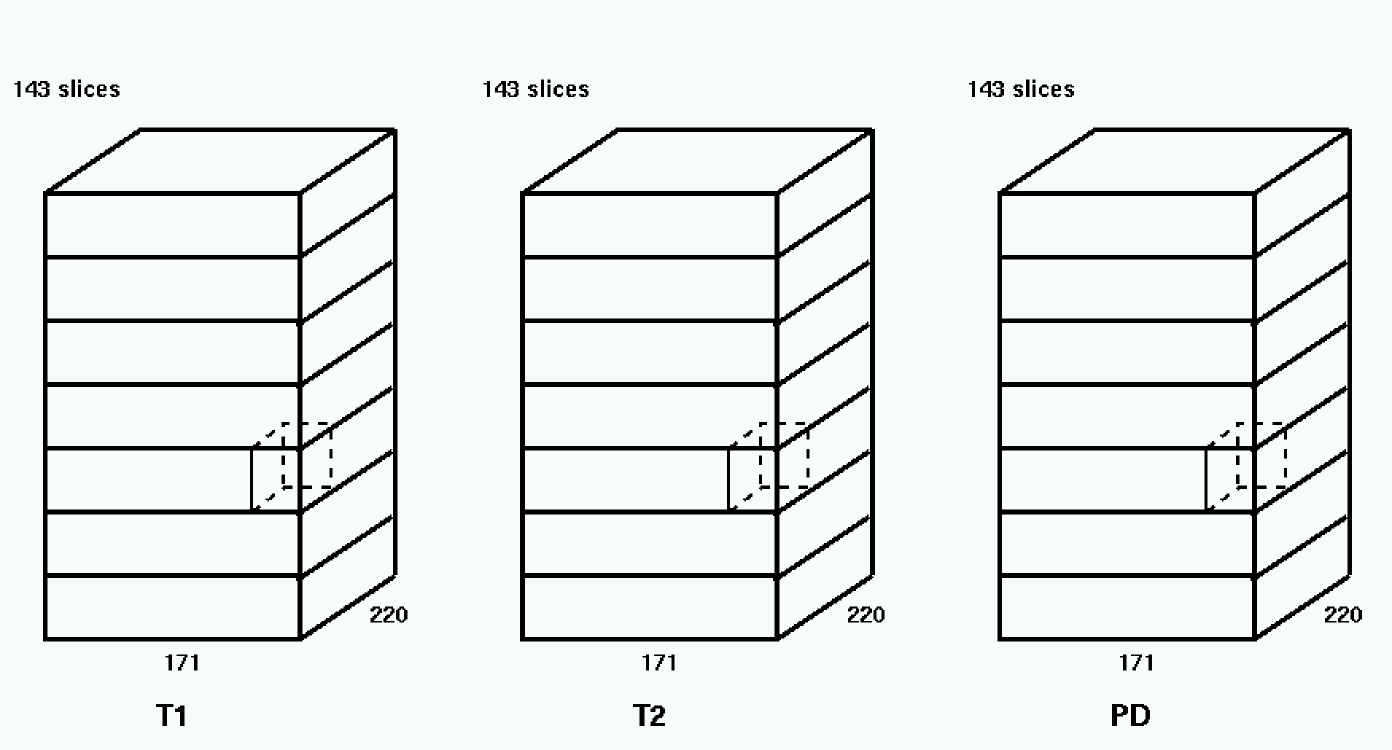
Leonardo Da Vinci (XV century) Studi anatomici

Digital Medial Images

- Computer Tomography
- Magnetic Resonance
- Positron Emission Tomography
- Single Photon Emission Tomography
- Angiography
- UltraSounds
- Digital Radiography, ...

Multimodal Medical Volumes (MMV)

Multimodal medical volumes can be obtained from a set of *d* different diagnostic volumes (such as MRI, PET, CT, etc.) by spatial *coregistration of volumes* in order to fully correlate complementary information (e.g., structural and functional) about the same patient.



Segmentation of multimodal medical volumes (MMV)

The visual inspection of a large set of such volumetric images permits only partially to the physician to exploit the available information.

Therefore, computer-assisted approaches may be helpful in the clinical oncological environment in order to delineate volumes to be treated in surgery.

The extraction of such volumes or other entities of interest from imaging data is named **segmentation** and is usually performed, in the image space, by defining sets of voxels with similar features within a whole multimodal volume.

MMV segmentation: rule based systems

low levels in image analysis:
physicians have difficulty to describe in linguistic form the rationale of their decisions

higher level in image analysis:
rationales of physicians are more precise, but strongly depend on many factors, e.g.
- different anatomical areas,
- different clinical frameworks,
- different theoretical approaches

difficult or impossible to settle the solution of the MMV segmentation problem in a reliable rule based systems framework

MMV segmentation: learning machines

Inference procedures based on **learning from data** must be then employed.

Supervised learning machines: Drawbacks

Learning needs the manual labeling of prototypical samples (training set)

time-consuming operation, even if the number of clusters is known.

inter-user and intra-user variability:
heavy biases may be introduced by unskilled or fatigued physicians

MMV segmentation: clustering

Unsupervised methods (clustering of the feature space):

• may *fully exploit the implicit multidimensional structure of data*

• *independent from the user's definition of training regions* due to their self-organizing approach (Bensaid et al., Gerig et al., 1992)

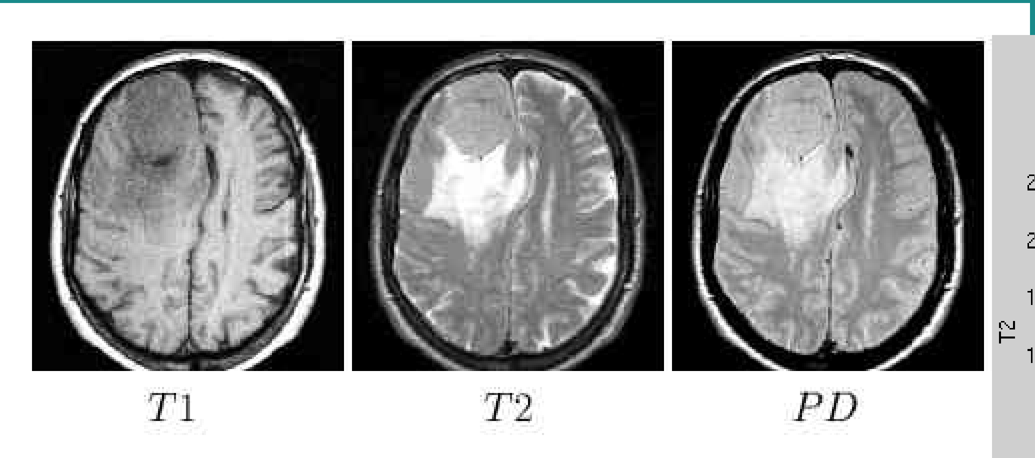
Image space and feature space

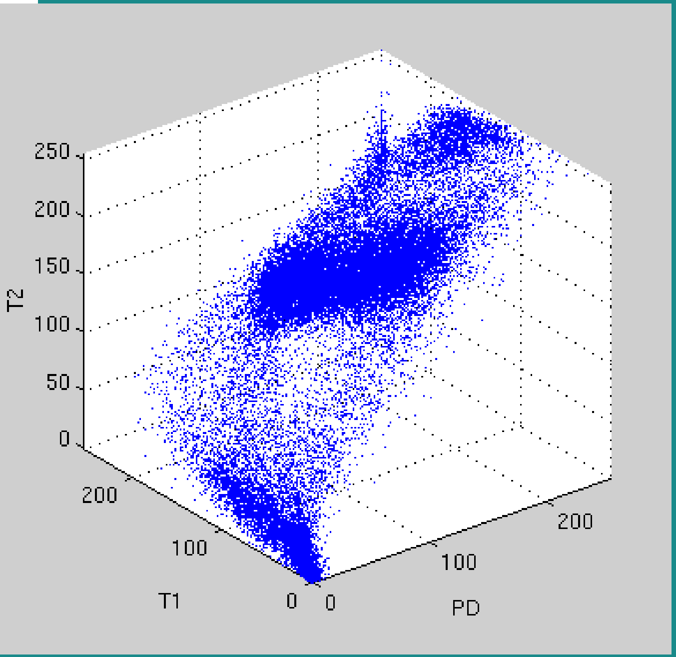
Multimodal volume: spatial registration of a set of *d* different imaging volumes.

Multimodal voxels are associated with an array of *d* values, each representing the intensity of a single modality in a voxel (*multimodal image space)*

The *d* different intensity values related to the multimodal voxel can be viewed as the coordinates of the voxel within an *d*-dimensional *feature space* where multimodal analysis can be made.

Example





Example: 3 co-registered MRI modalities

The interplay between the *multimodal image space* and the *feature space* turns out to be very important in the task of understanding the data structure.

Main steps in segmenting MMV

- **Definition of clusters** within the *d*-dimensional feature space
- **Classification of all the voxels** of the volumes to the resulting classes

Approach more robust to noise in discrimination of different tissues than techniques based on edge detection (Bezdek et al.,1993).

Bias effects

Many bias effects must be taken into account in considering clustering for the segmentation of medical images, e.g.:

• Very *heterogeneous clusters* may be found in the feature space, with very different probability densities $\Rightarrow$ considering the cardinality of clusters in the clustering process.

• *Partial volume effect during acquisition* may produce a really intrinsic ambiguity of borders between regions of interest.

Interactive graphical system for MMV segmentation

Two conflicting requirements to be balanced:

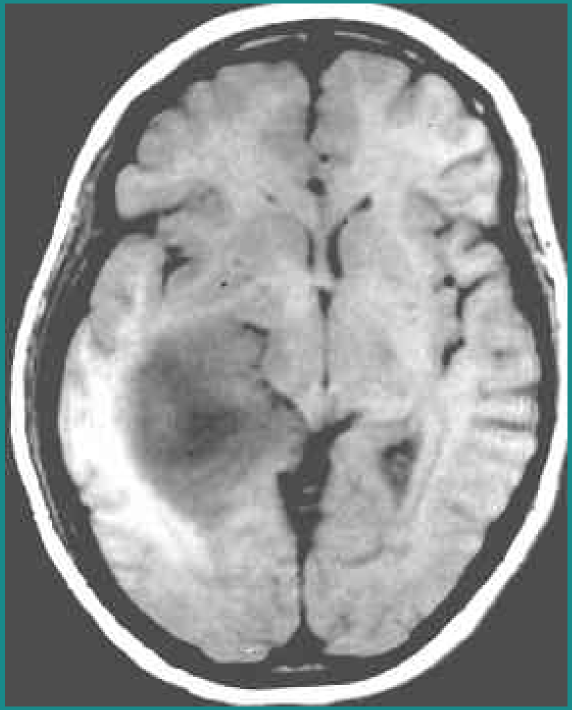
elimination of noise and redundancy from original images	↔	preservation of significant information in the segmented image.

To this aim, we have developped an *interactive graphical system for MMV segmentation* (Schenone, et al.,1996; Masulli et al.,1999) that allows the physician user to

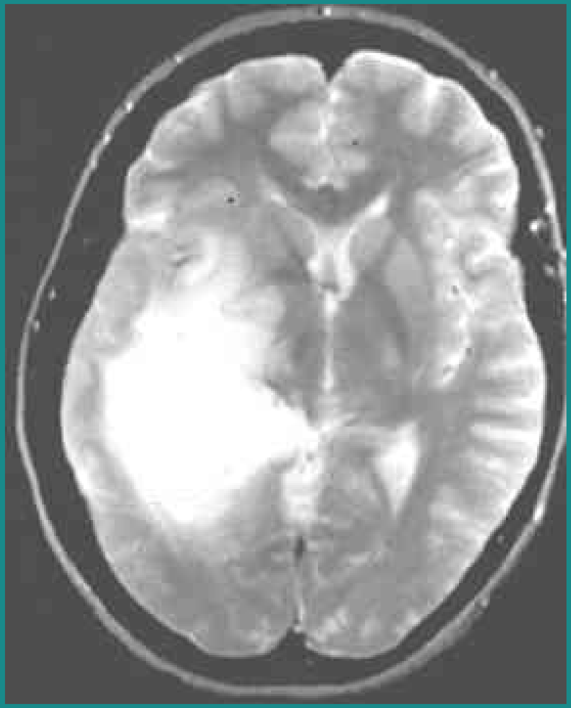
- *introduce his/her medical knowledge* in the analysis sequence in order to balance the two conflicting requirements and
- *stay in control* of both of the decions sequence and the results in the analysis process.

Experimental analysis - *Data set*

Multimodal transverse slice of the head composed by spatially correlated MRI images from a head acquisition volume of a patient with glioblastoma multiforme in the right temporal lobe



T1-weighted MRI



T2-weighted MRI

288 x 362 pixels

256 gray levels

sligth bad coregistration !!

From the BRIGHAM-RAD data base

Notes

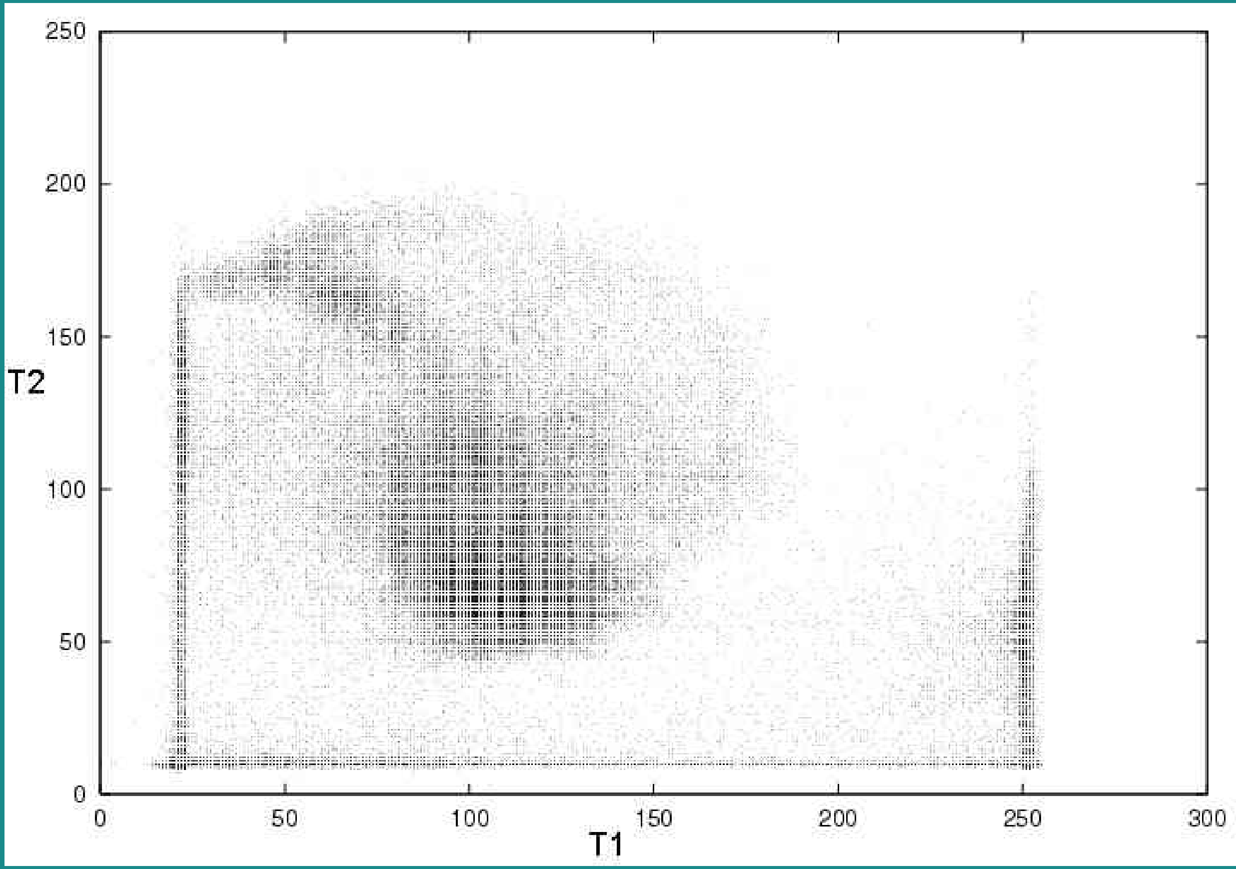
- The tumor is located in the right temporal lobe and appears bright on the T2-weighted image and dark on the T1-weighted image.
- A large amount of edema is surrounding the tumor and appears very bright on the T2-weighted image.
- The lower signal area within the mass suggests tissue necrosis.

Feature space

Each pixel in the above defined two-modal slice is associated to an array of two intensity values (T1 and T2).

$\Rightarrow$ each of these couples of pixel intensity is represented by a point in a 2D feature space, whose coordinates represent the intensity values in that pixel of each modality belonging to the multimodal set.

Feature space



Feature space (T2 versus T1)
obtained from the MRI images

Segmentation task

The 7 main classes in the data set are:

- white matter
- gray matter
- cerebro spinal fluid (CSF)
- tumor
- edema
- necrosis
- scalp.

The segmentation task consists in finding the main classes in the feature space and in associating each pixel in image to one of these classes.

The slight mis-registration between images may be responsible of some mis-classification errors in final results.

Methods: CM

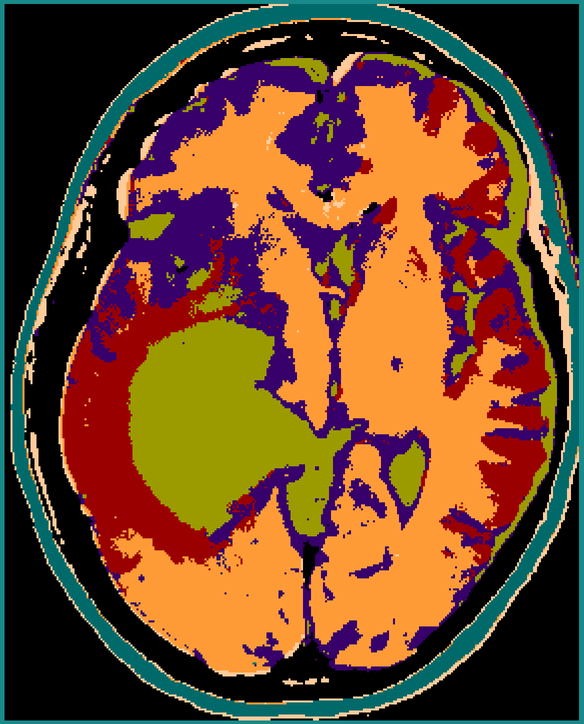
- 7 clusters
- tolerance for the stop criterium $\varepsilon_1 = .01$
- centers of clusters initialized at random
- convergence is noticed in 10-15 fast iterations.

Results: Segmentation by the CM algorithm

Problem of local minima.

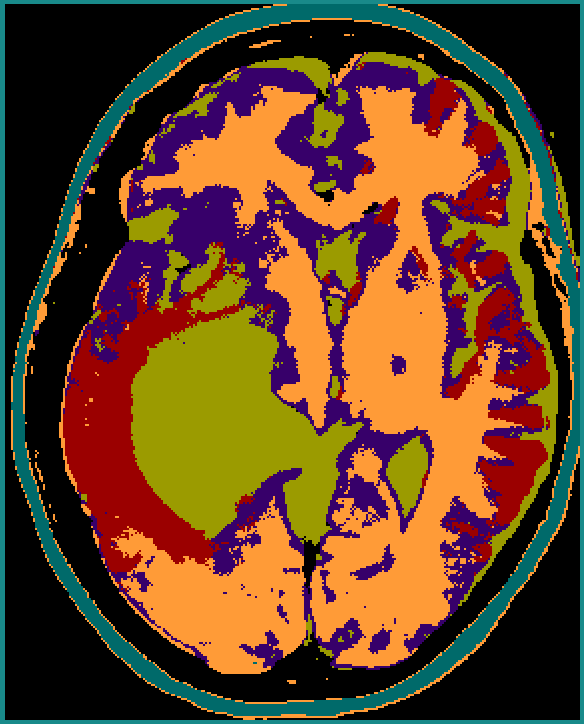
Concerning best solution:

- Almost correctly scalp definition.
- White matter too extended
- **Mistakes in classification** of gray matter and edema in the right side of brain
- Not able to separate tumor, necrosis and CSF.



CM-7 clusters - Best result

Results: Segmentation by the ESCM algorithm using J_w



ESCM using J_w - 7 clusters.

Similar results than best CM.

Better definition of white matter.

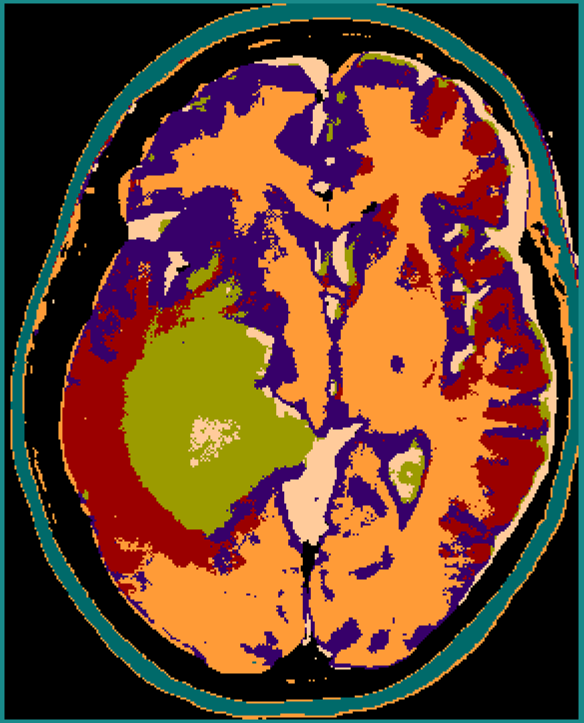
From a large number of tests, ESCM results to be largely **more stable than CM** with respect to the positions of centroids and to the extension of clusters in the feature space.

Results: Segmentation by the ESCM algorithm using J_s

Taking into account the cardinality of clusters, the results dramatically improve.

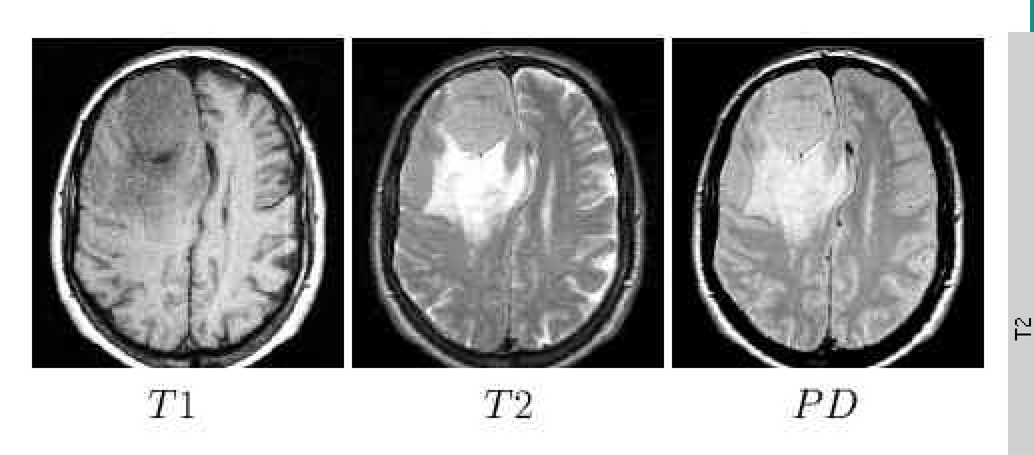
Correct *distinction between tumor and CSF*, and within the tumor region is able to *find the necrosis region*.

Correct definition of scalp and white matter and misclassification in the right side of the brain as from CM.

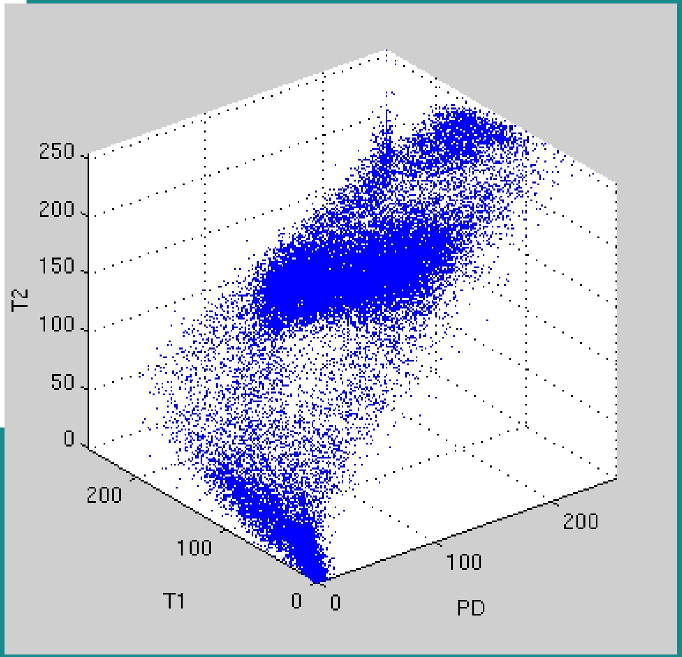


ESCM using J_s
7 clusters.

Set of 3 MRI

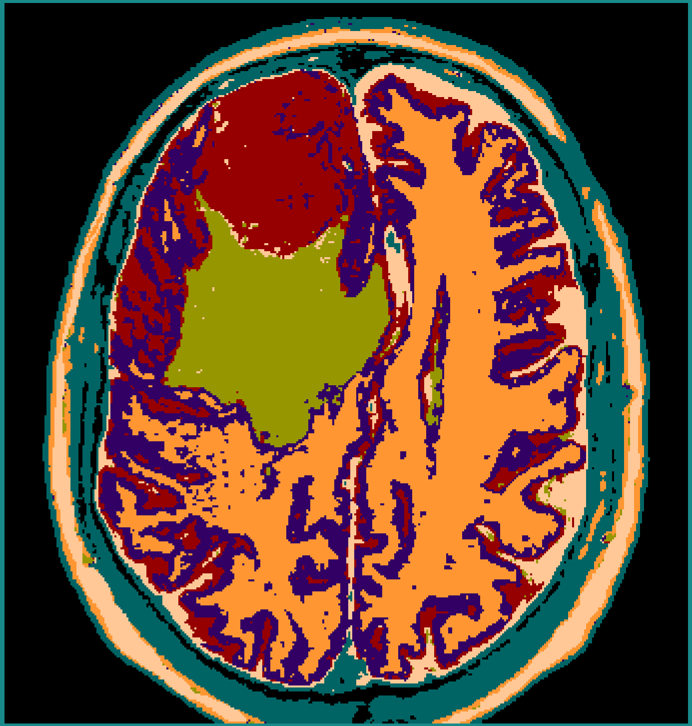


3 co-registered MRI modalities

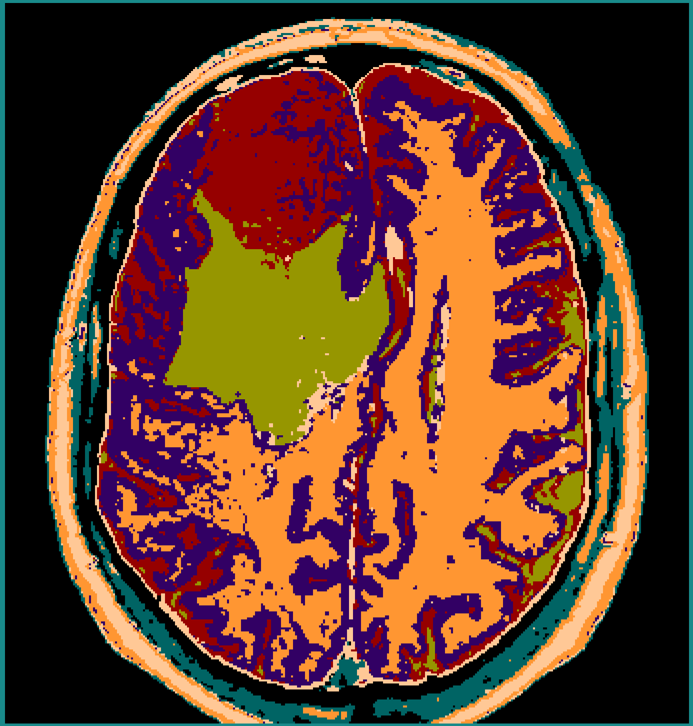


Feature space

Results on the set of 3 MRI



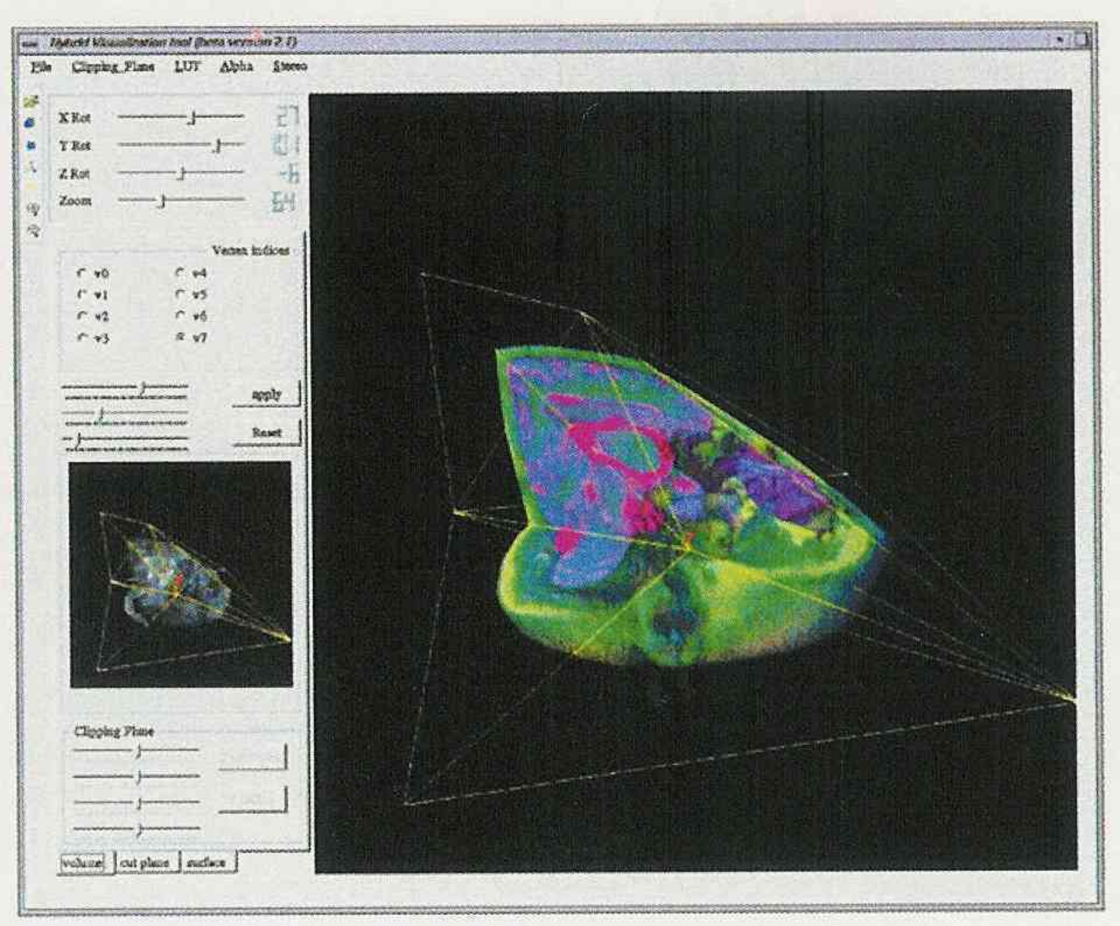
Possibilistic C-Means



ESCM

Graphical Interface (1/4)

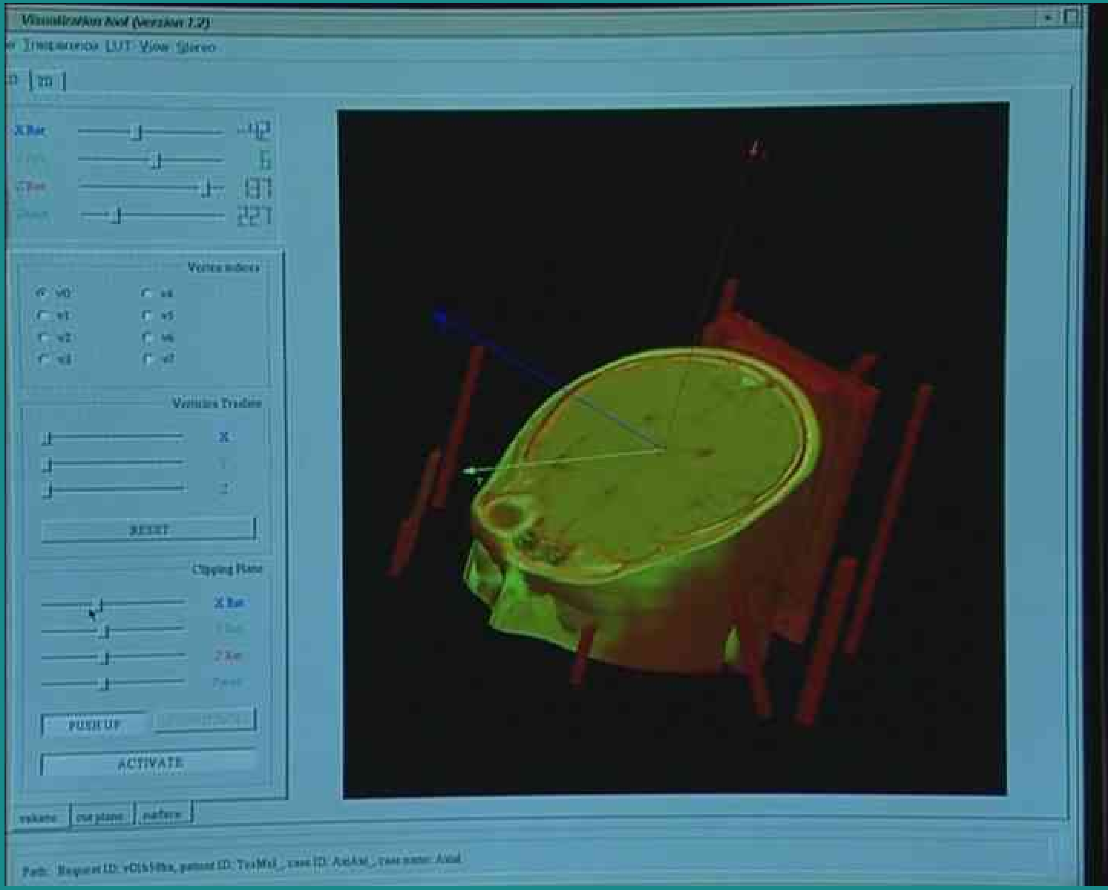
Through the graphical interface, the clinicia can intervene by changing the segmentation results both in space and in the image of features and can apply various algorithms for 3D visualization and navigations



Graphical Interface (2/4)

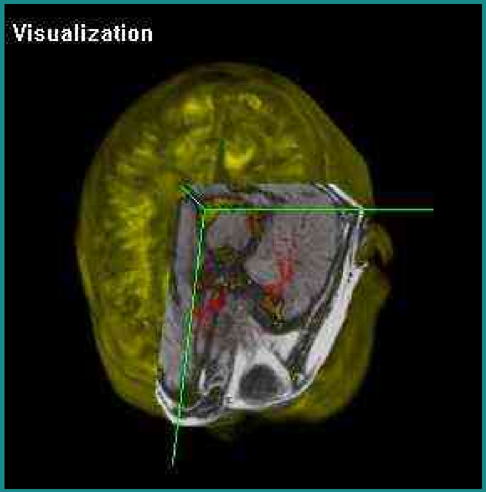
Transparenza

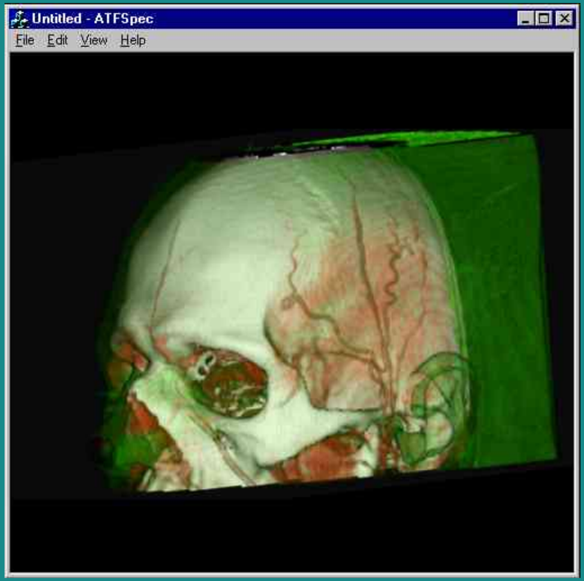
- Stereographic views
- Views of volumes and surfaces
- Rotation, zoom, cutting planes
- transparency

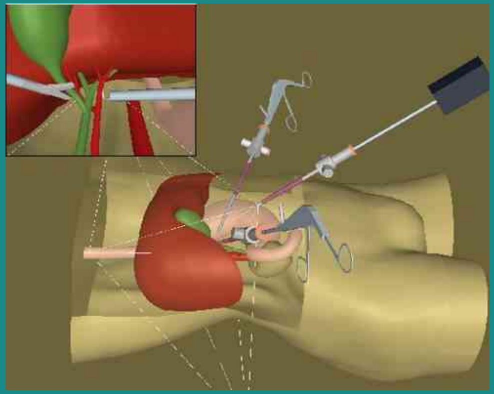


Graphical Interface(3/4)

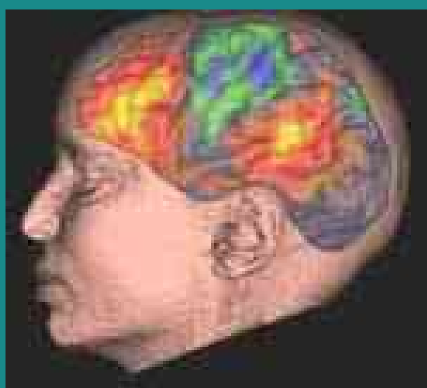
- Surface rendering
- Volume rendering

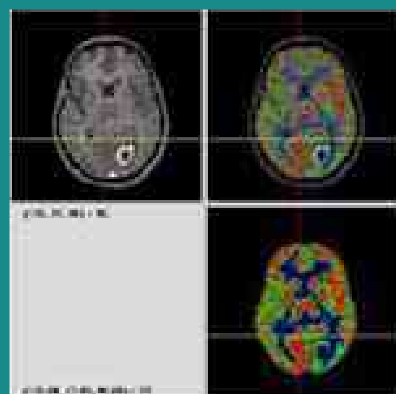


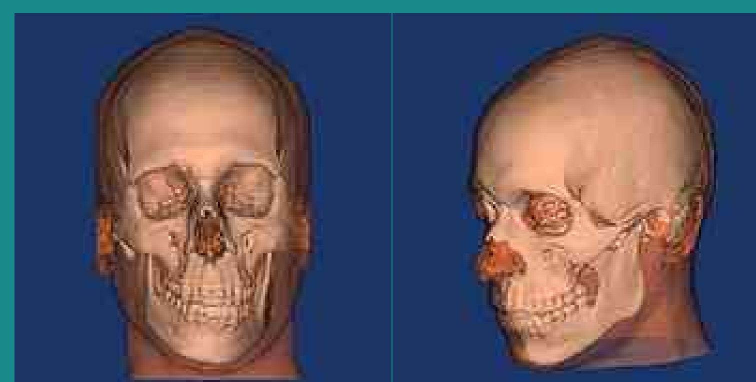




Graphical Interface (4/4)

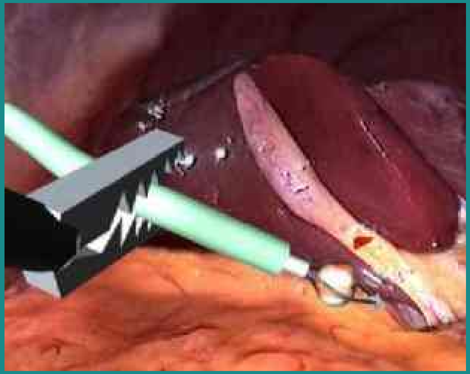


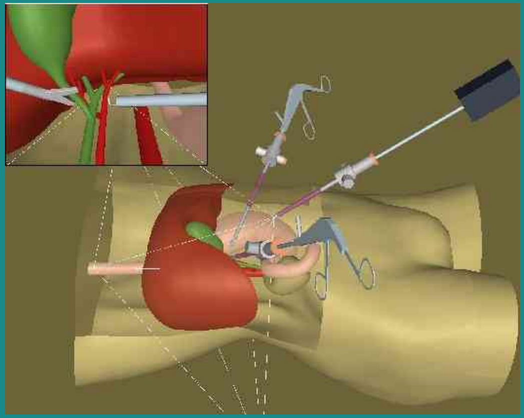




Computer Guided Surgery

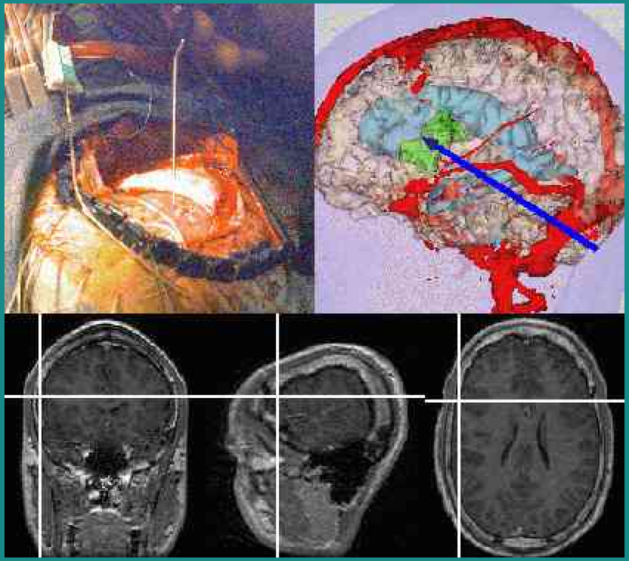
Simulation





Computer Guided Surgery

Intraoperatory support



Training in surgery

learning-by-doing
cooperative

complex decisions
manual skills
technological skills