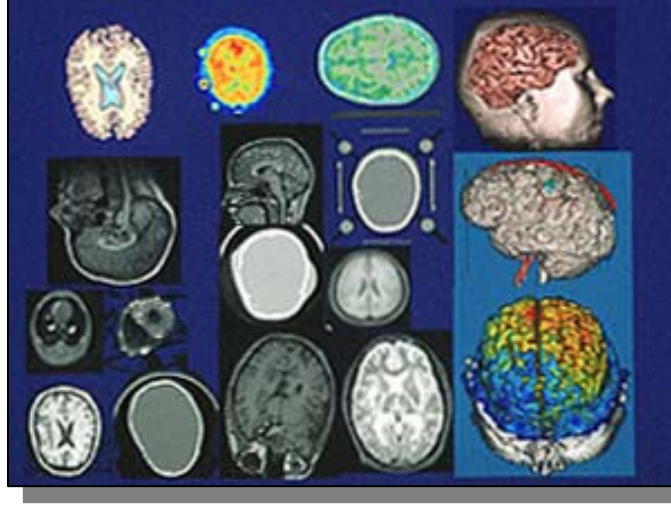

Medical Imaging II:

Data Fusion in 3D Medical Imaging

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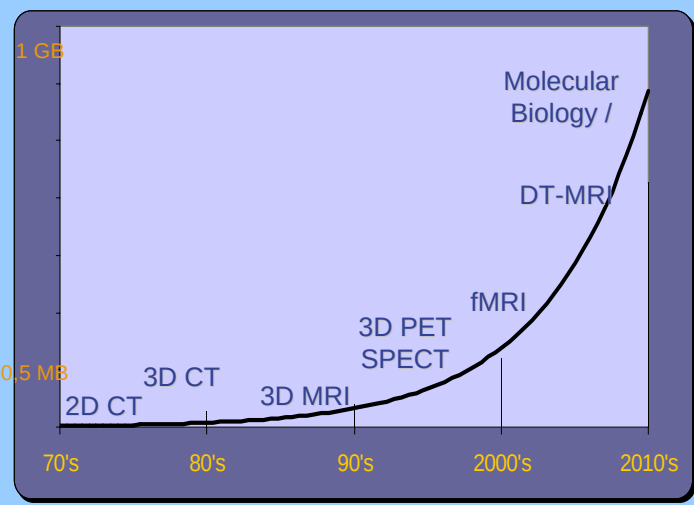
Plan

- General Context
- Illustration of Data Fusion Issues
- Principal of Data Fusion in 3D Medical Imaging
- Image Registration
  - Basic Concepts
  - A Focus on Deformable Registration
    - Local, Global and Hybrid methods
- Cooperation between segmentation and registration tasks
- Perspectives
  - Deformable registration
  - Sharing heterogeneous and distributed resources

General Context and Challenges

- Context :
  - Expansion of the quantity of data produced and processed in medical imaging (« *from the volume to the mass* »)
  - Explosion of the IST and the electronic communication resources
- Challenges :
  - To guide the clinician (e.g. a neurologist) within the mass of information to integrate into the medical decision process
  - To guide the surgeon for the exploitation of the different sensors and effectors (e.g. robots) to use in the interventional theater



- MS lesions
  12000 images*/patient/year
- Epilepsy surgery
  7000 images*/intervention

*: 1 image = 1 2D MRI slice

Coming issues

- To conceive the surgical room of the future
  - Intra-operative multimodal sensors & effectors (e.g. robots) at macro, micro and nano scales
  - To manage the sources of information from observation & knowledge
- To better understand the healthy and pathological states of organs at different scales (*human physiome*)
  - Imagery of pathologies : from the gross organ to the molecule
  - Modeling healthy and pathological group of individuals from selected image descriptors (*computational anatomy and function*)
- To connect people and medical resources thru high band networks and pooling of information sources for:
  - Discovering unlikely events
  - Data mining and knowledge discovery
  - Validation and certification of new drugs

Research issues

- Need to interconnect medical information resources (data, programs, medical devices) together:
  - Data fusion of medical images
  - Merge semantic and computational Grid technologies
  - Development of new adaptive medical devices (*effectors, sensors, …*)

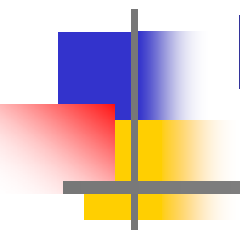
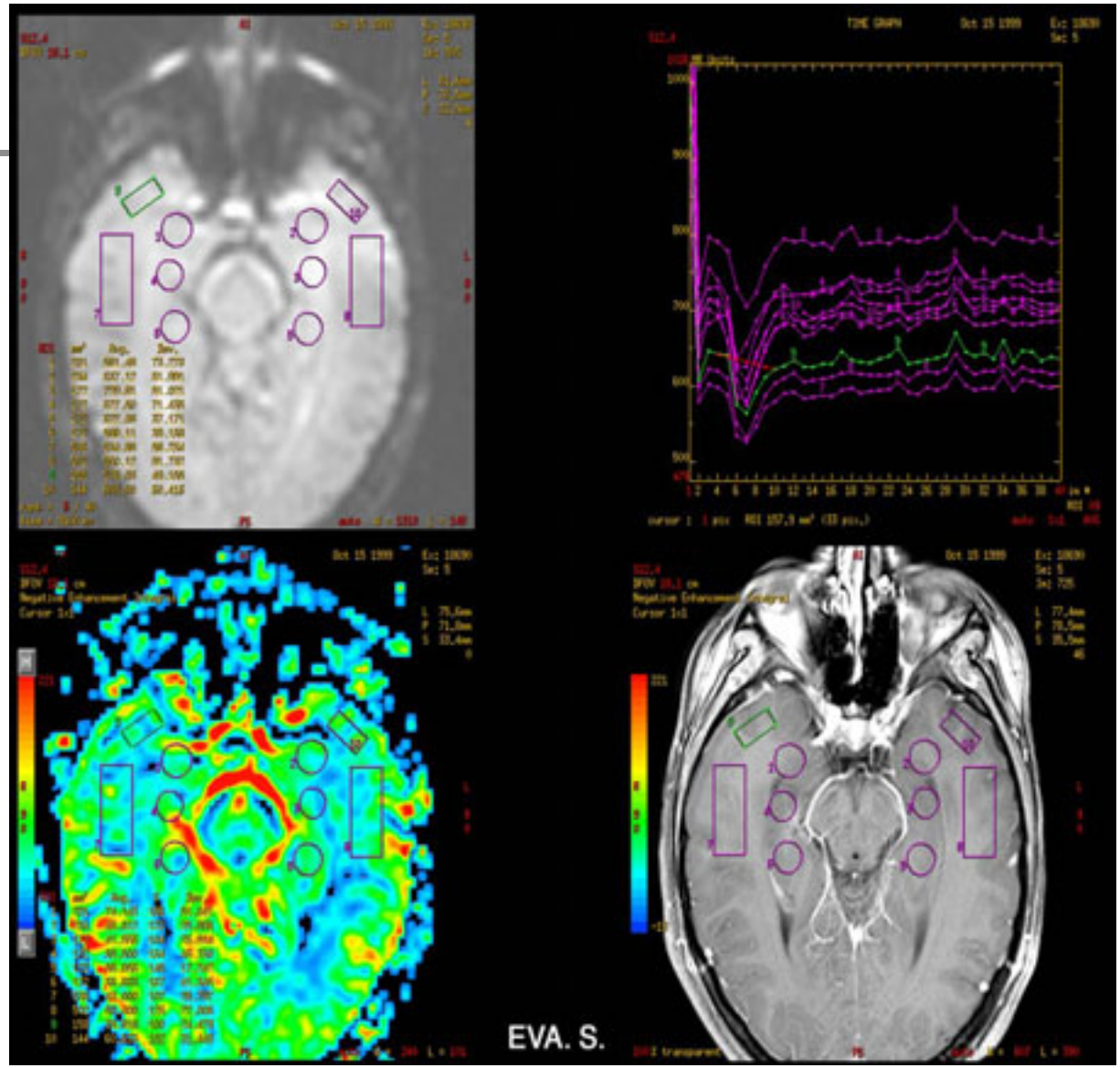


Illustration of Data Fusion Issues

Epilepsy Surgery

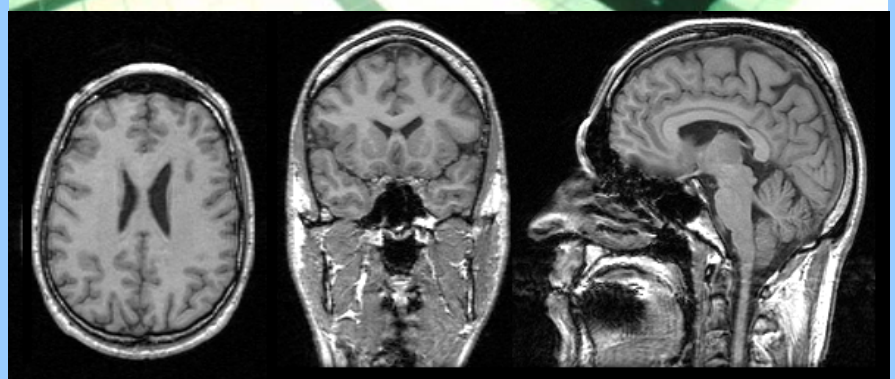
- Patient selection
- Semiology of crisis and relations to anatomy
- « Static » Exams (*search of lesions*)
- « Dynamic » Exams (*search of epileptogenic status*):
  - Interictal : functional imaging, Electrodes Implant
  - Ictal : Crisis Recordings and labeling
- Presurgical Planning
- Cortectomy (surgery)

« Static » Exams

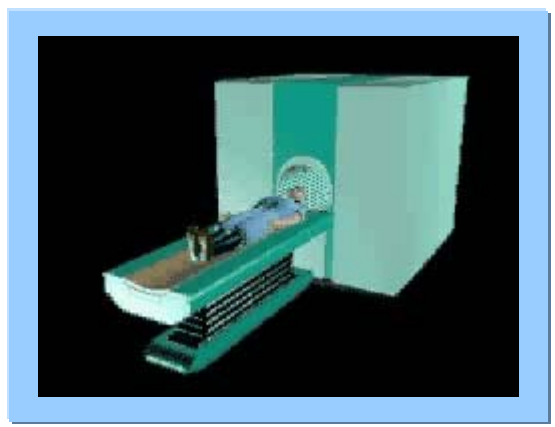


(Source: [A. Biraben *et al.*, CHU Rennes])

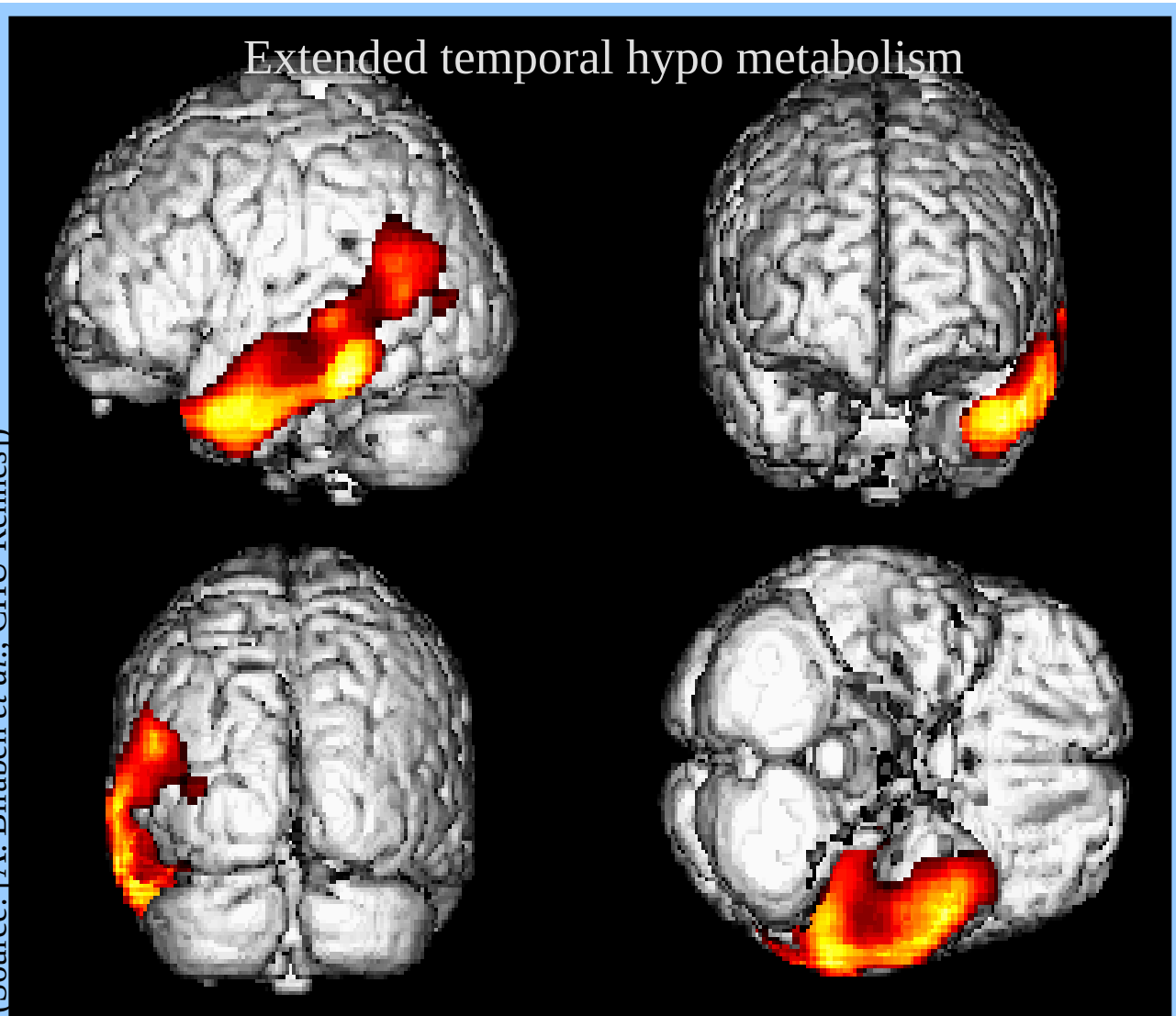
Magnetic Resonance Imaging (MRI)



- Proton Density - NMR
  - 256 x 256 pixels (1mm resolution)
  - From 20 to 120 slices along three axis

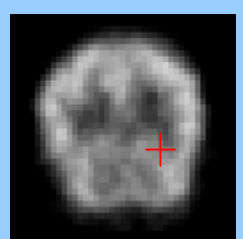


«Dynamic» Metabolic Exams



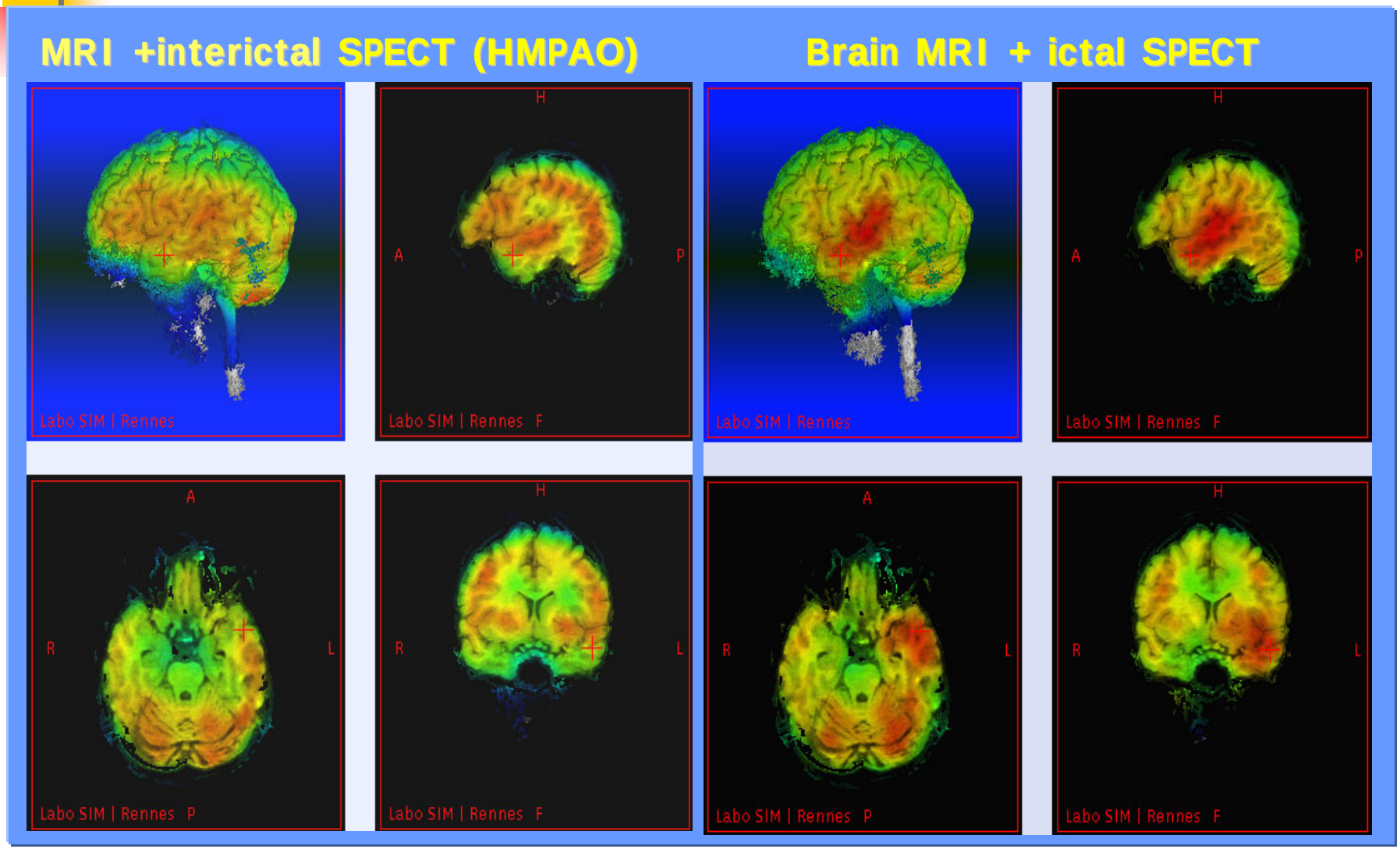
(Source: [A. Biraben *et al.*, CHU Rennes])

Single Photon Emission Computed Tomography (SPECT)

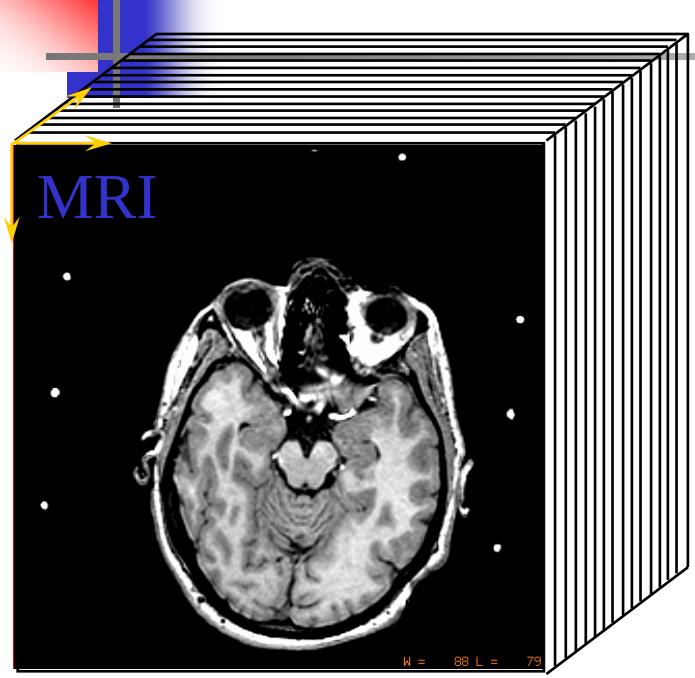


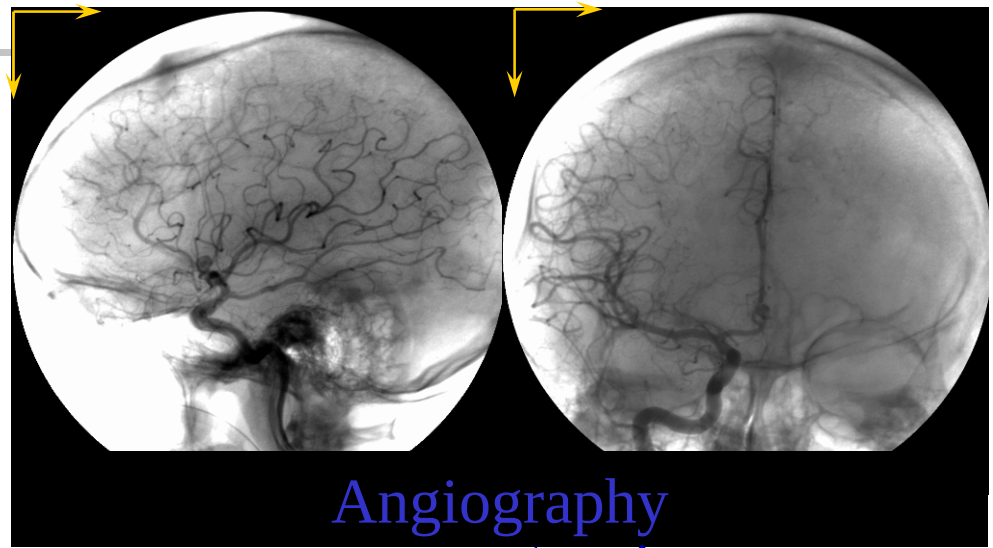
- Distribution of a radio tracer
  - Typical 64 x 64 à 128 x 128 pixels (resolution 3 to 5mm)
  - 64 to 128 slices per volume

Fusion of “Static” and «Dynamic» Exams



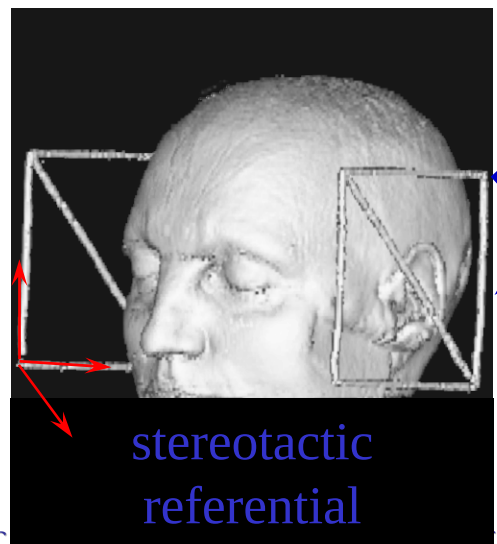
Intra cerebral electrodes implant in stereotactic conditions





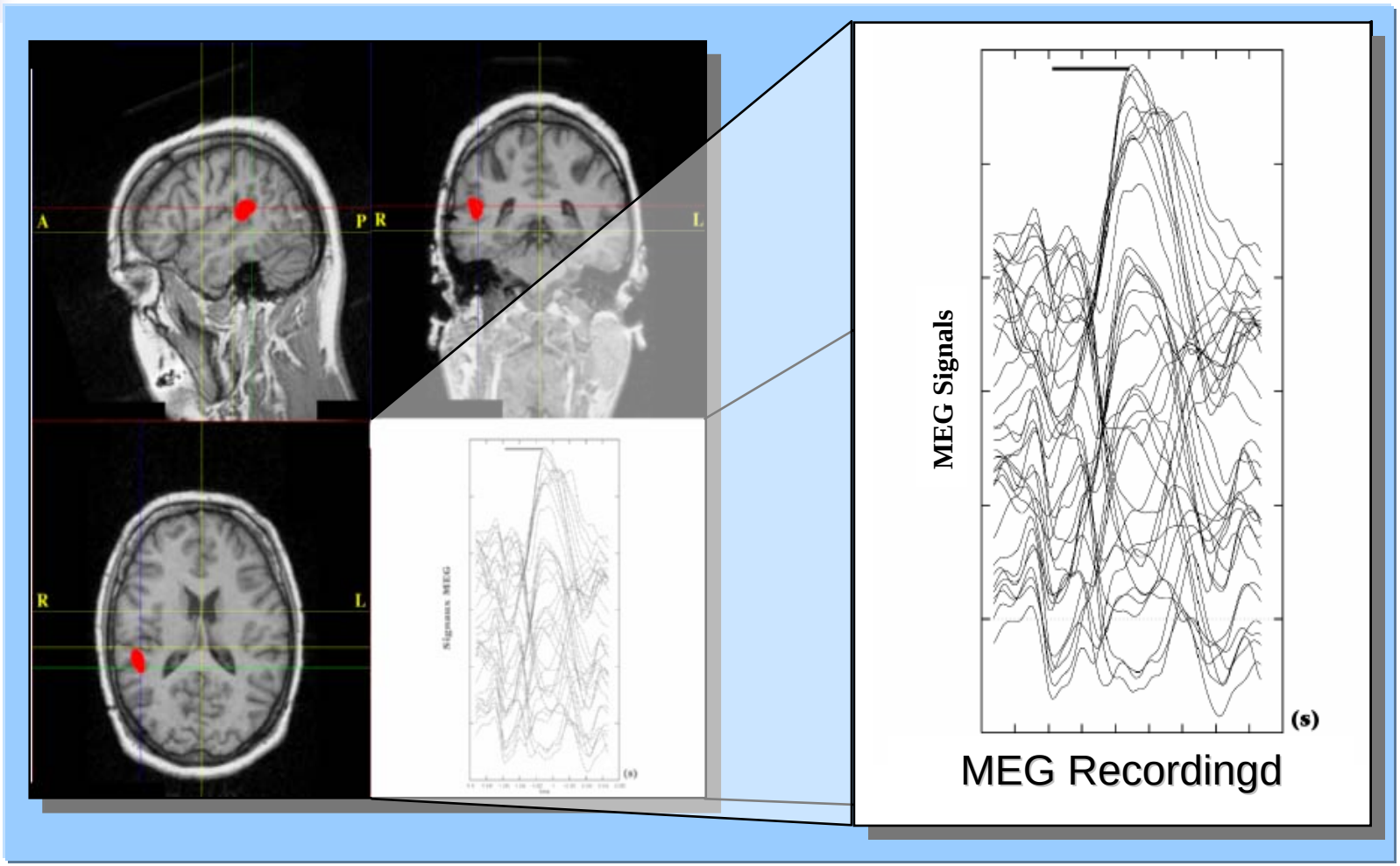
Registration of 3D referential

3D - 2D Projections



Intra cerebral electrodes recordings

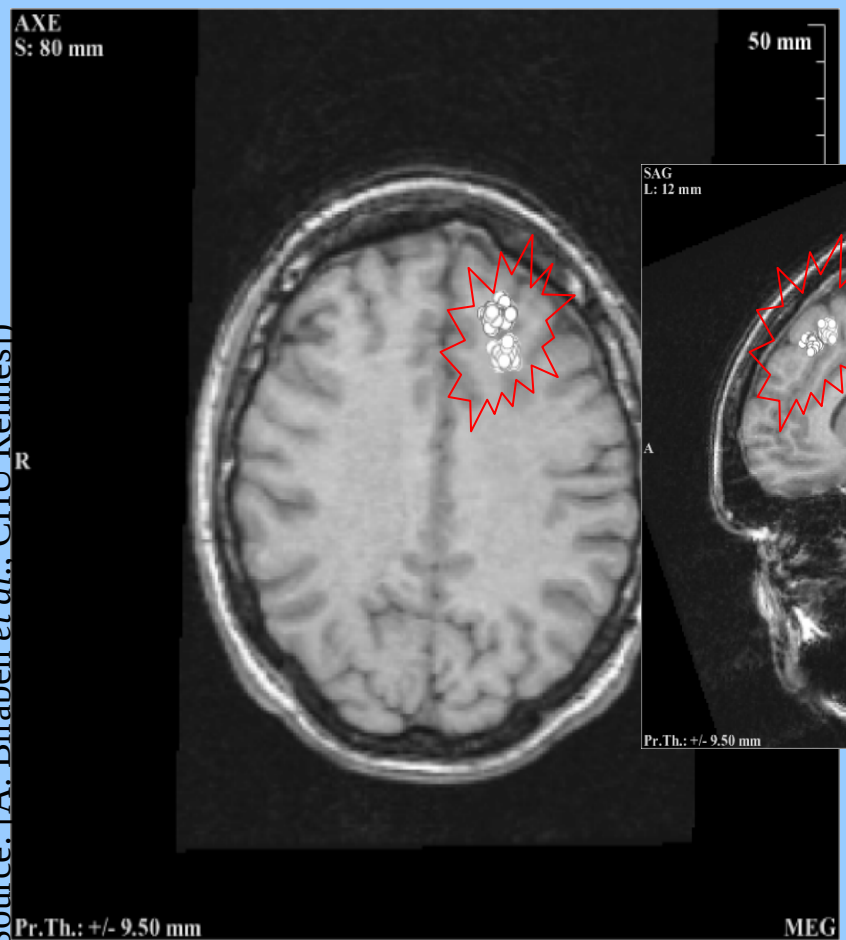
Dynamic Exams and Pre-operative Planning:
Functional recording of epileptic region environment

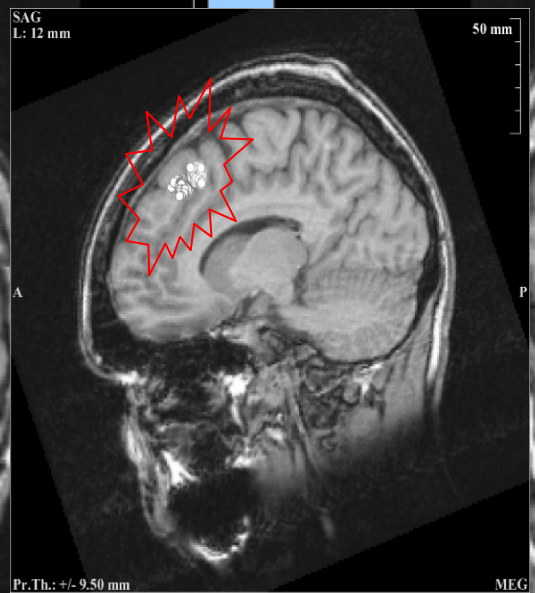


Functional Imaging : MagnetoEncephaloGraphy (MEG)

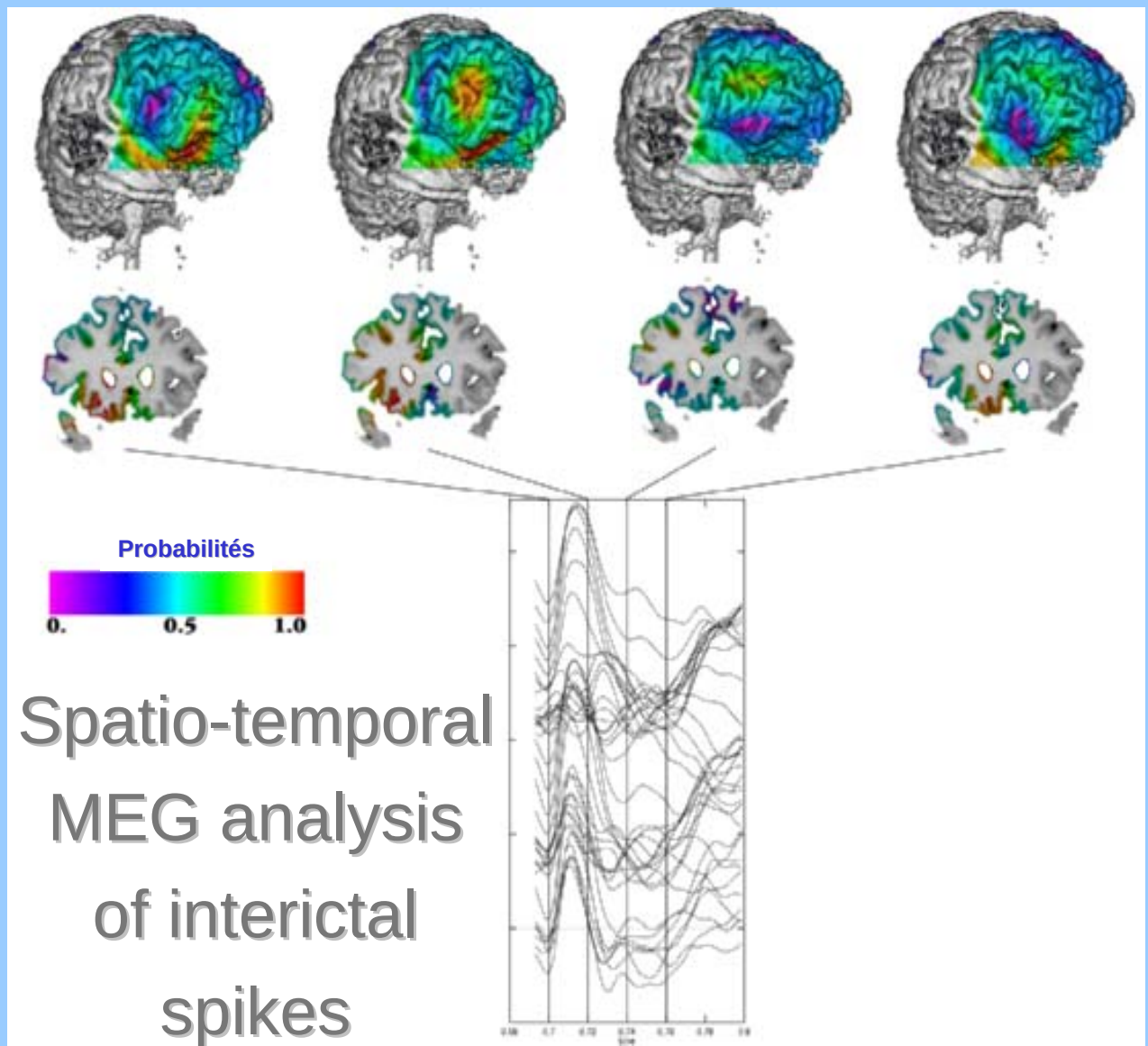
- Measure of the magnetic field issued by the neuronal activity :
  - Brain : 10^{-13} Tesla
  - Hearth : 10^{-3} Tesla
  - MRI : 1 to 3++ Tesla
- 40 to 150+ sensors (SQUID)
- spontaneous and evoked potentials, e.g.:
  - motor
  - somesthesic
  - language
  - visual

Interictal MEG





(Source: [A. Biraben *et al.*, CHU Rennes])

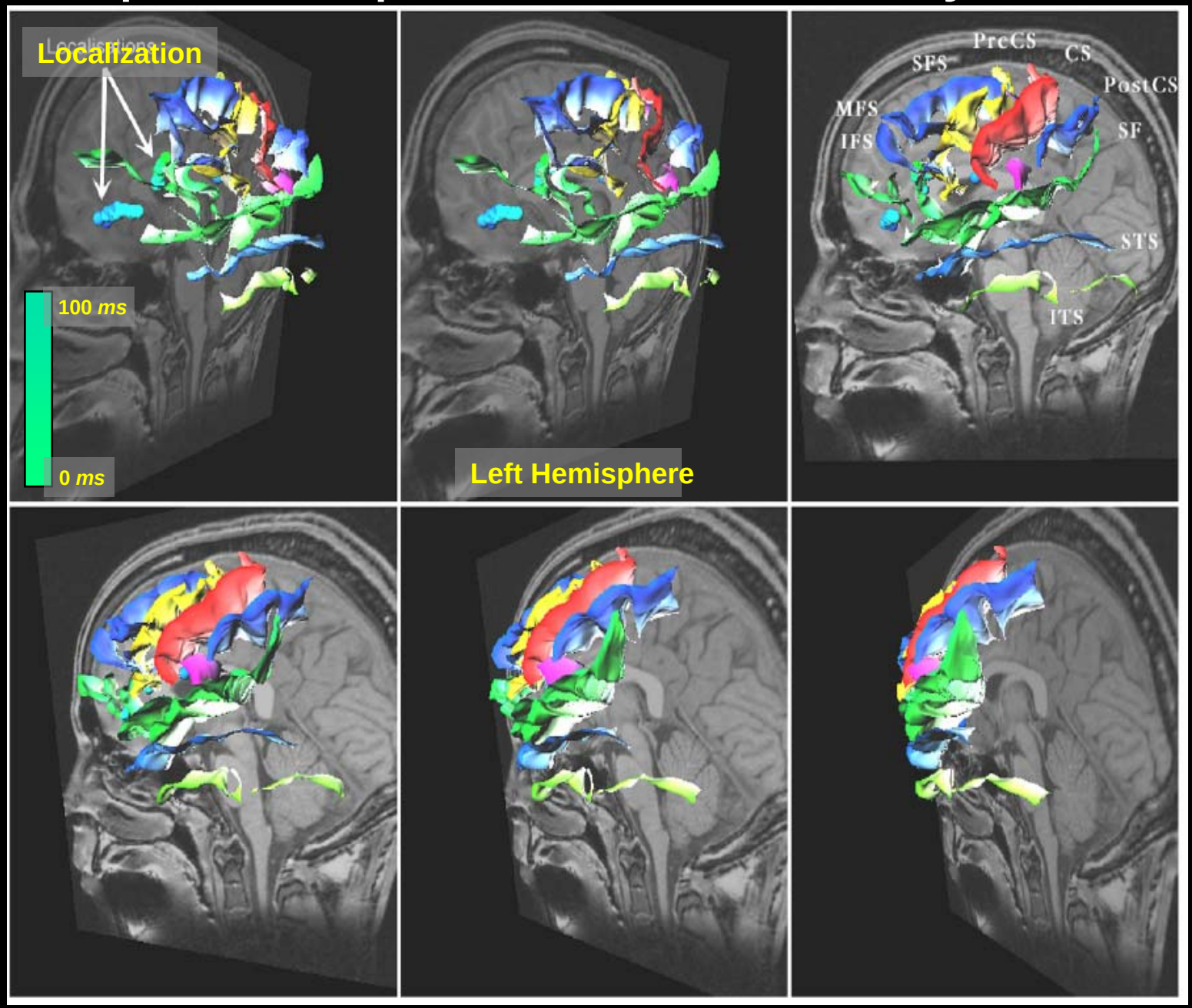


Spatio-temporal MEG analysis of interictal spikes

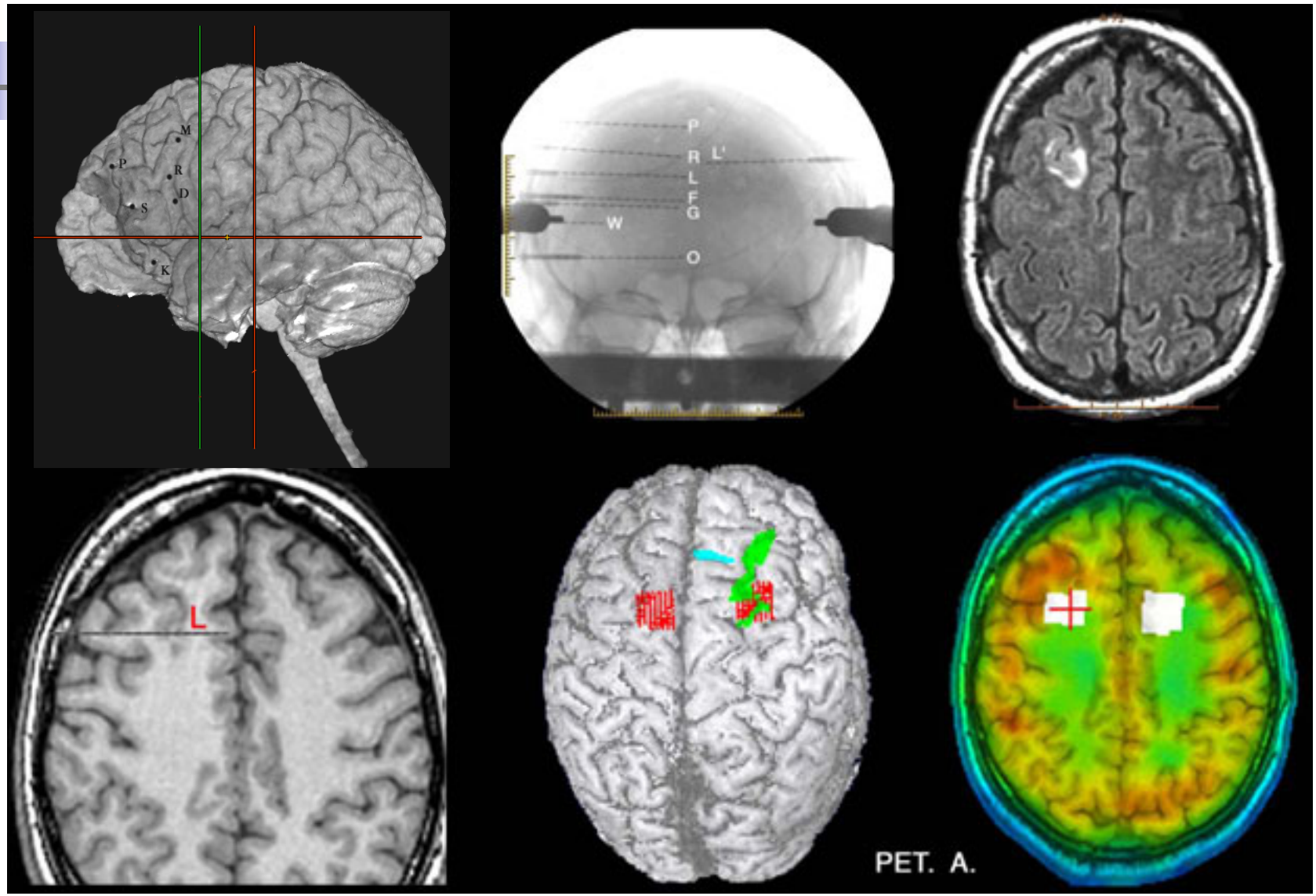
[Source : D.P. Schwartz, et al., Neuroimage:*Functional Mapping of the Human Brain*, 7(4):S466, 1998]

MEG : Spatio-temporal analysis of interictal spikes

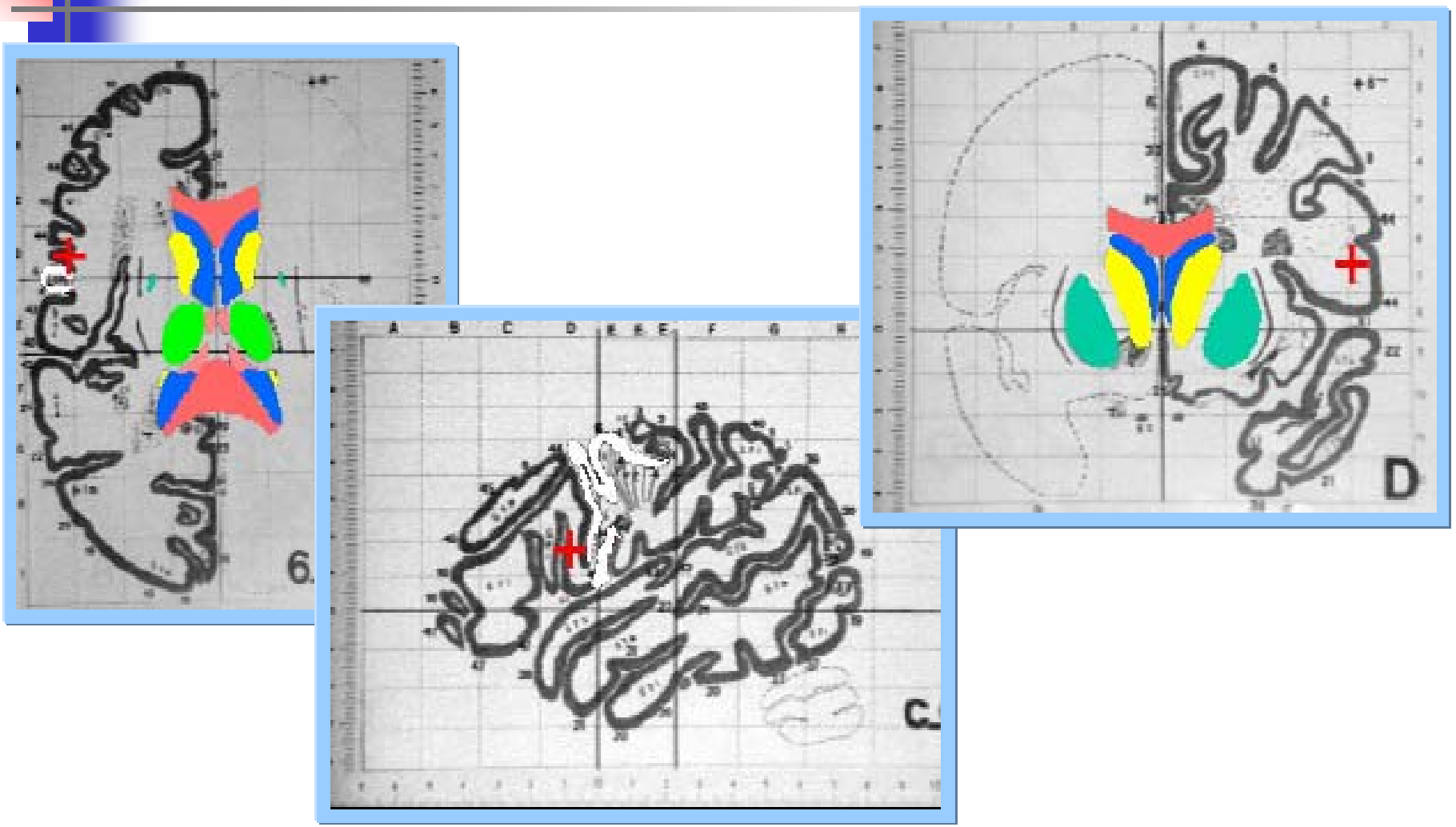
MEG : Spatiotemporal Interictal Analysis



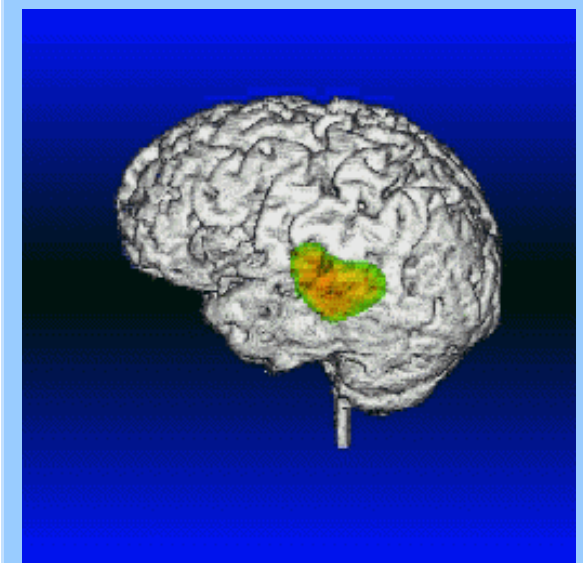
Epilepsy Surgery : Preoperative Planning

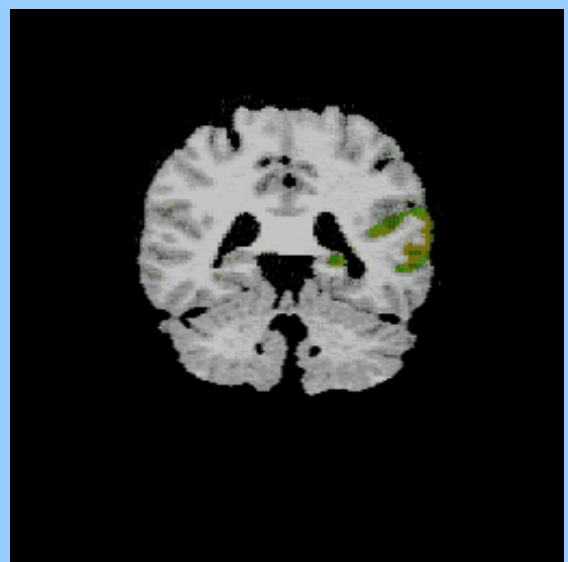


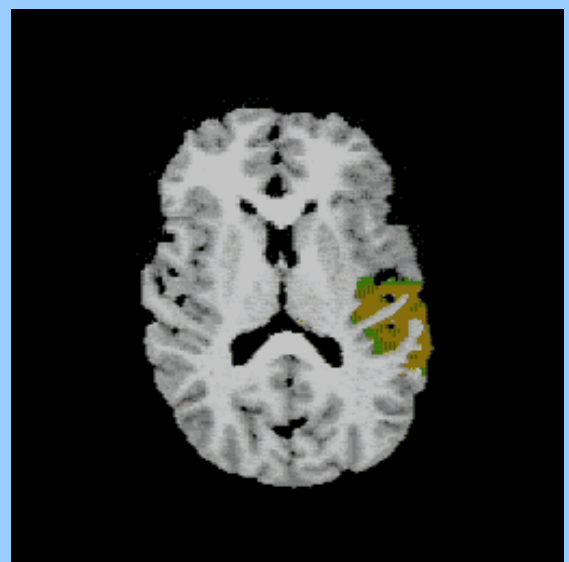
Talairach Atlas



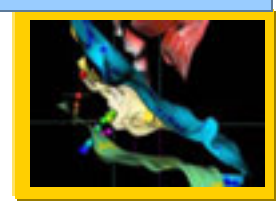
Functional Mapping of language areas

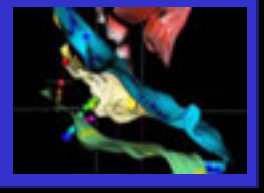


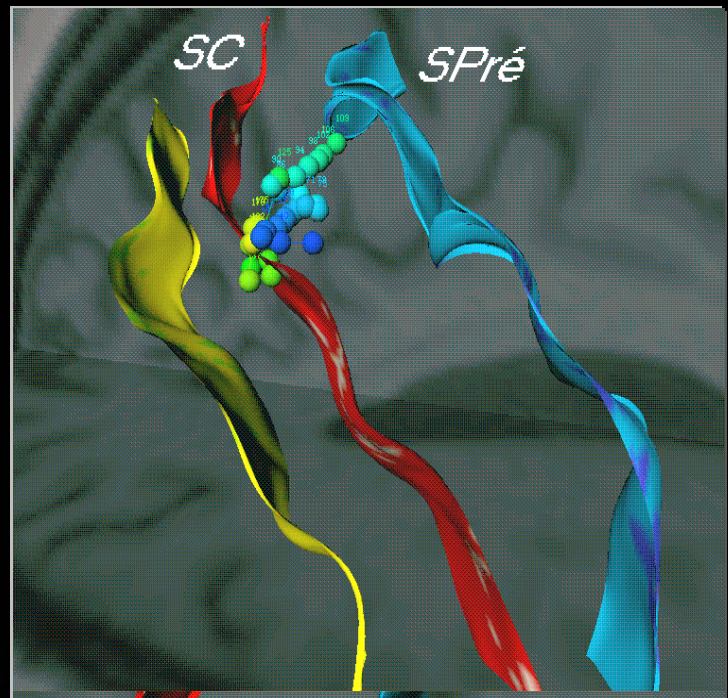


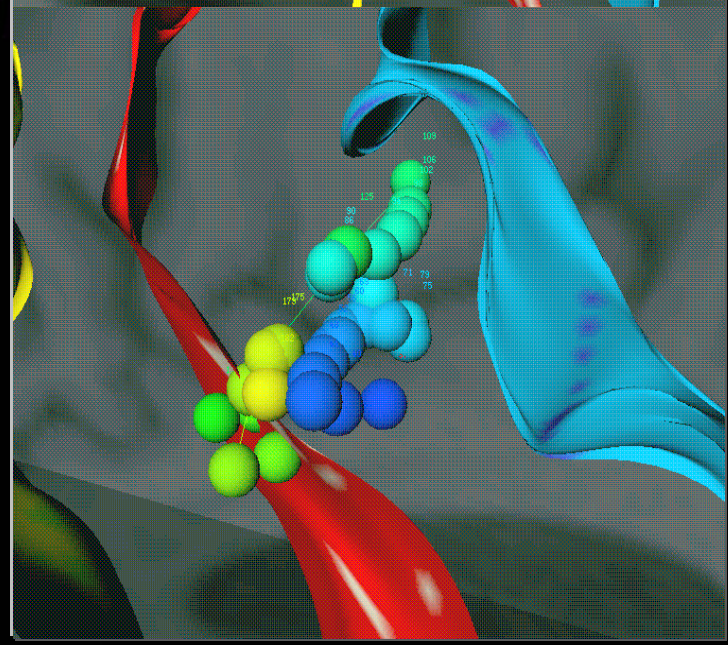


Silent *vs* Active Word Activation



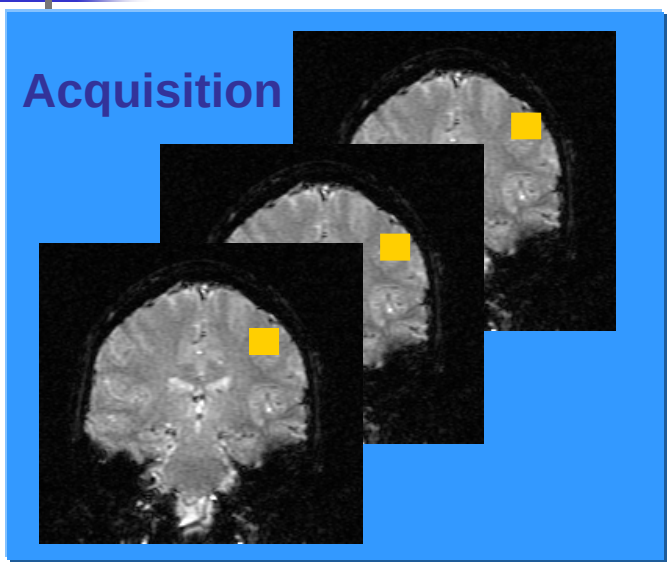


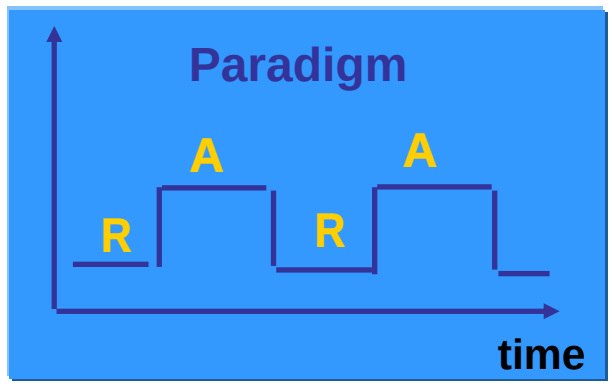


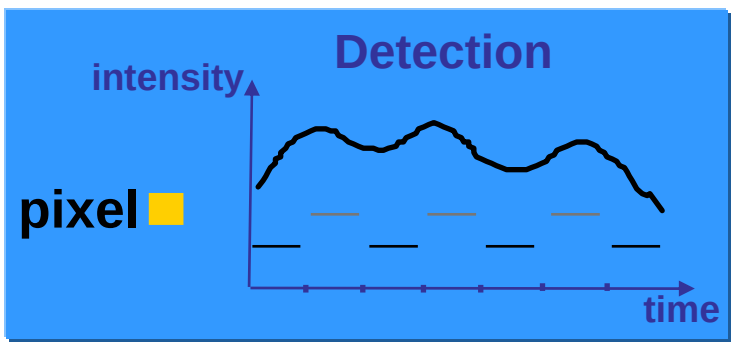


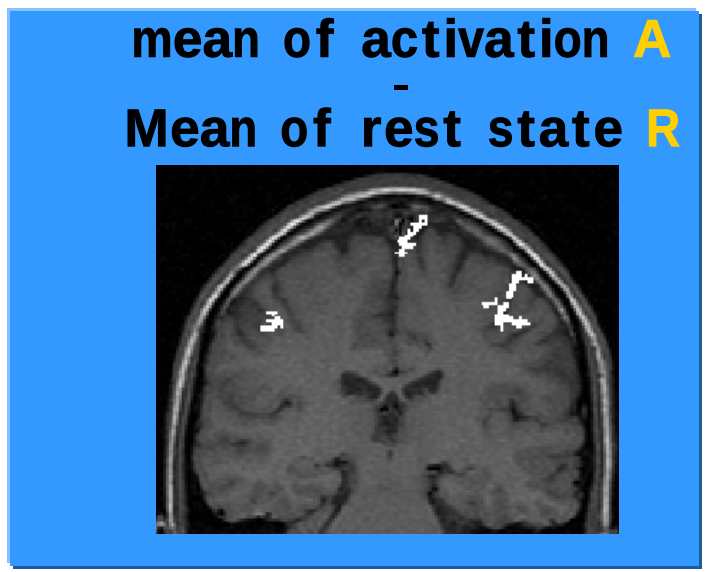
XM - Left (Silent Word Generation)

Preoperative Planning : functional MRI (fMRI)









Epilepsy Surgery:
Superposition of graphical data

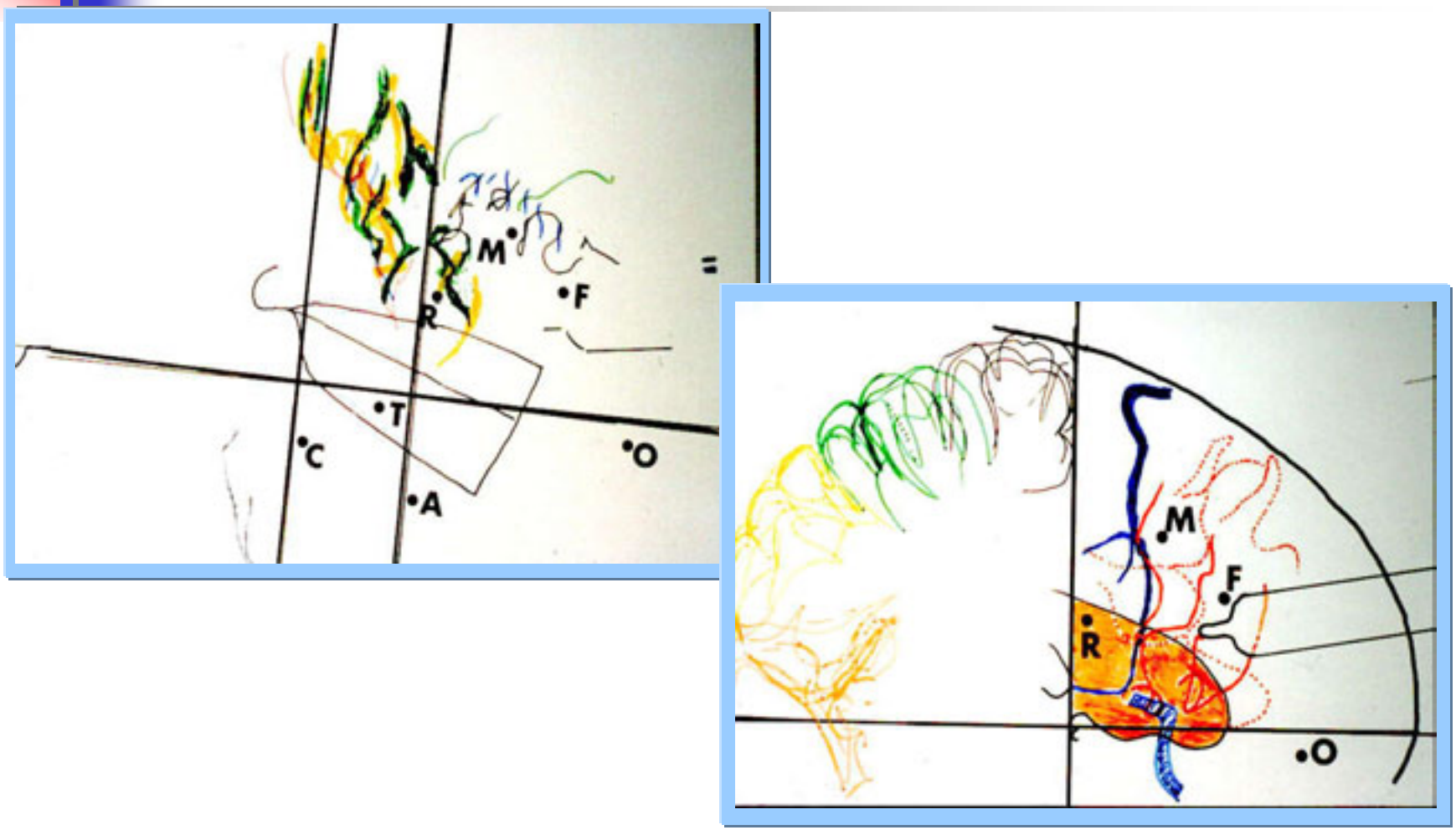
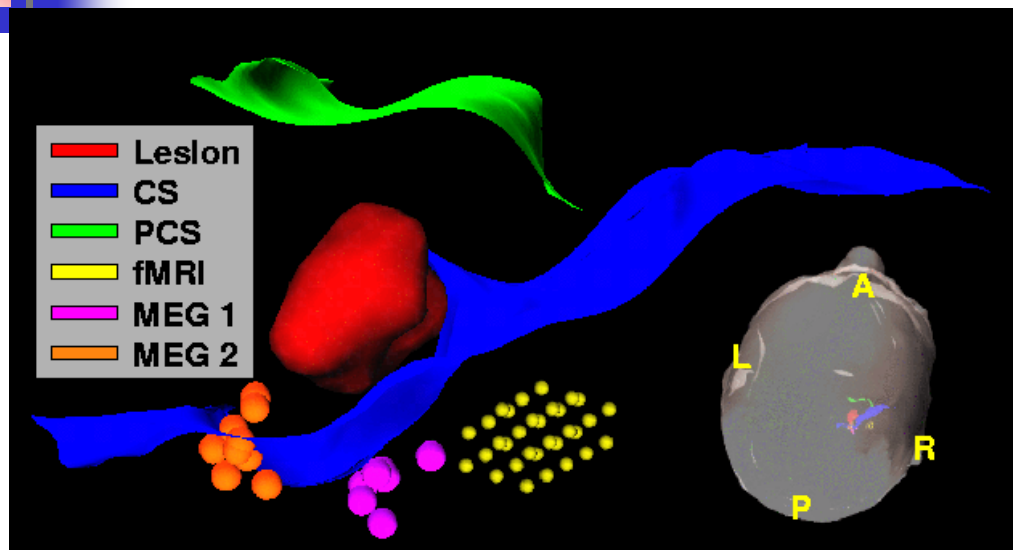
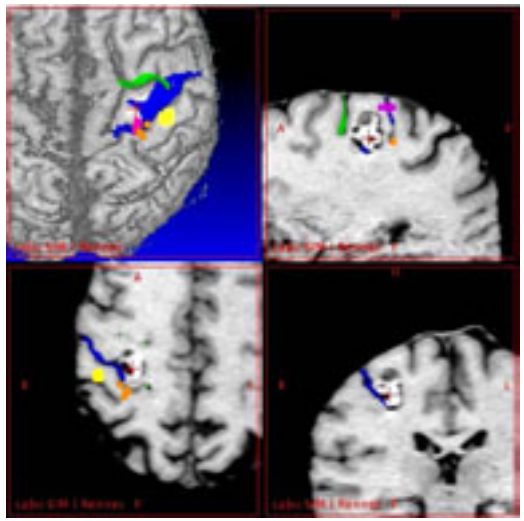
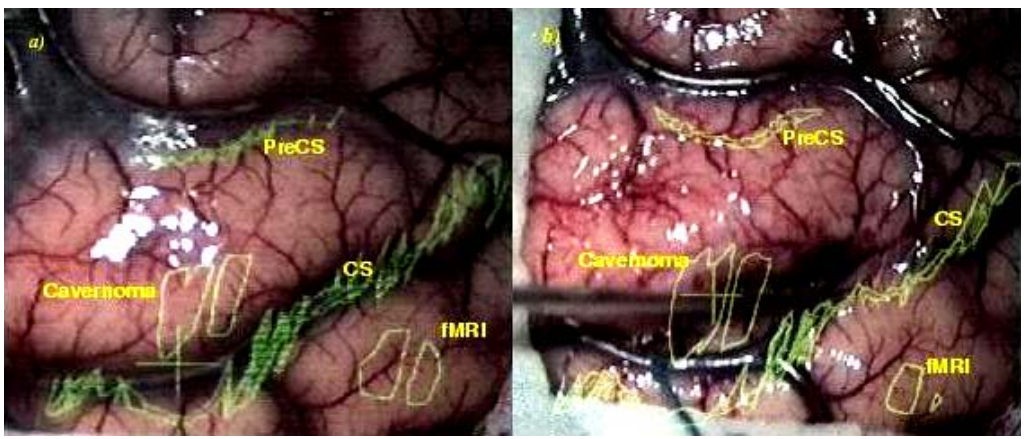
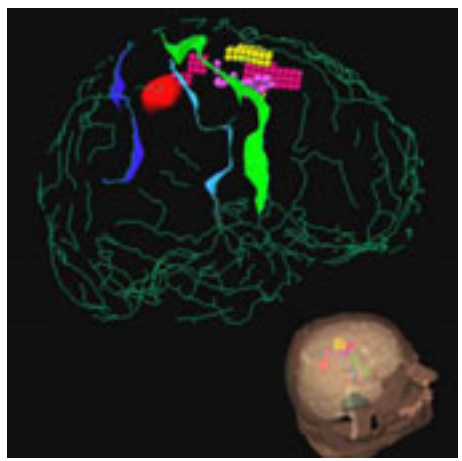


Image Guided Surgery

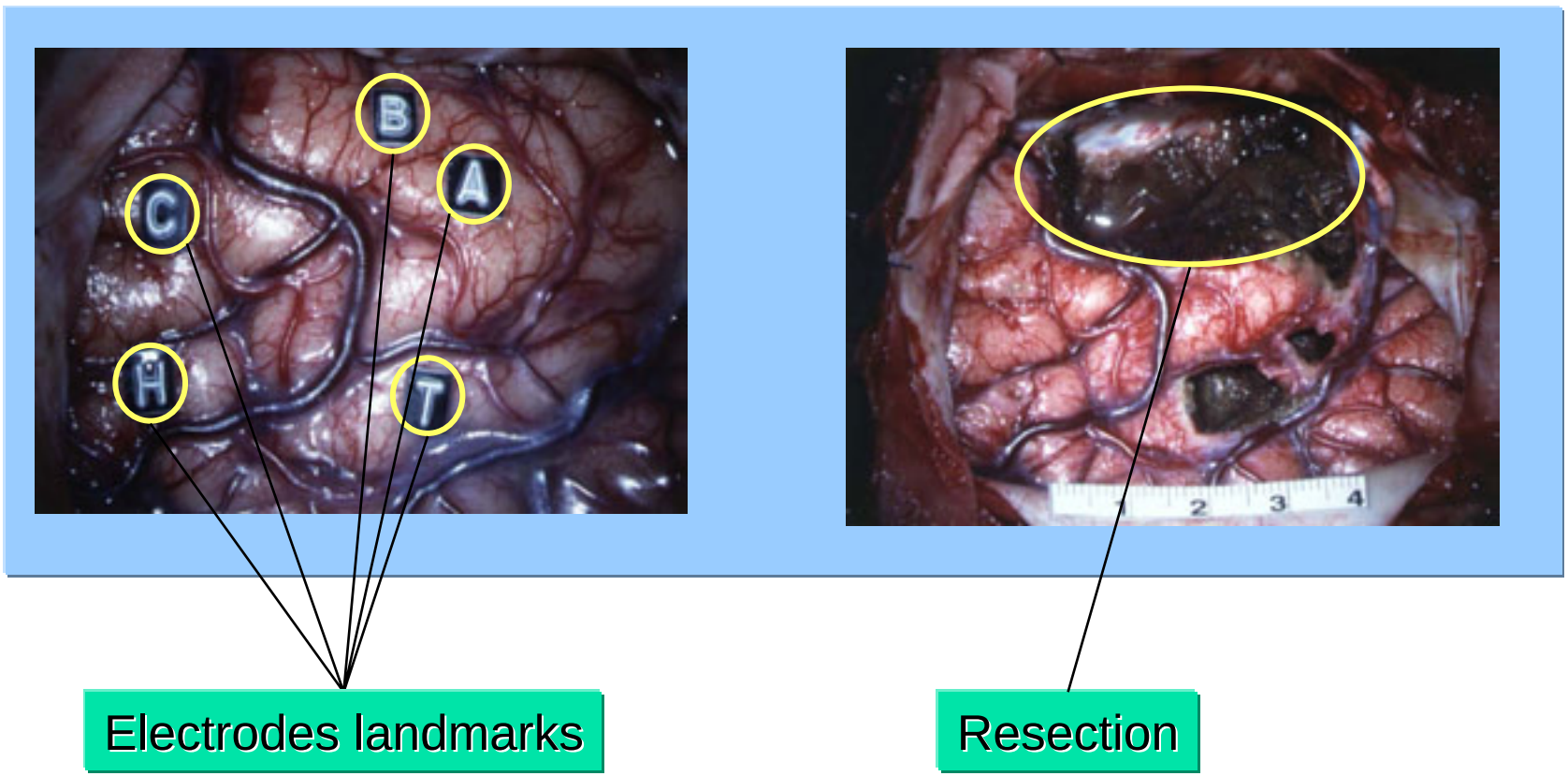








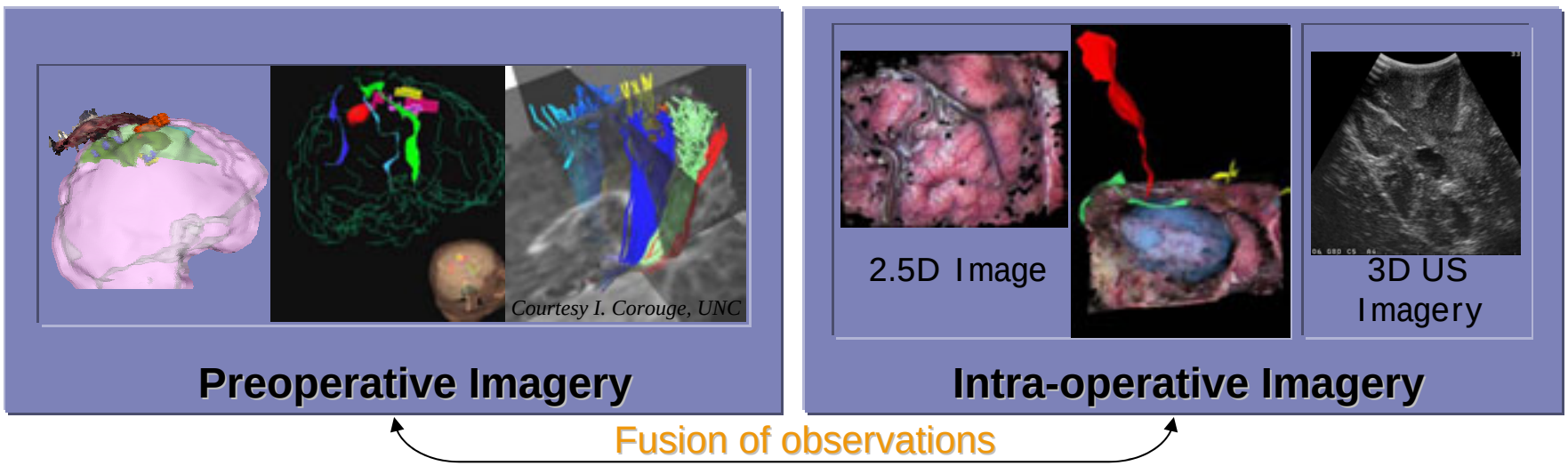
Surgical resection



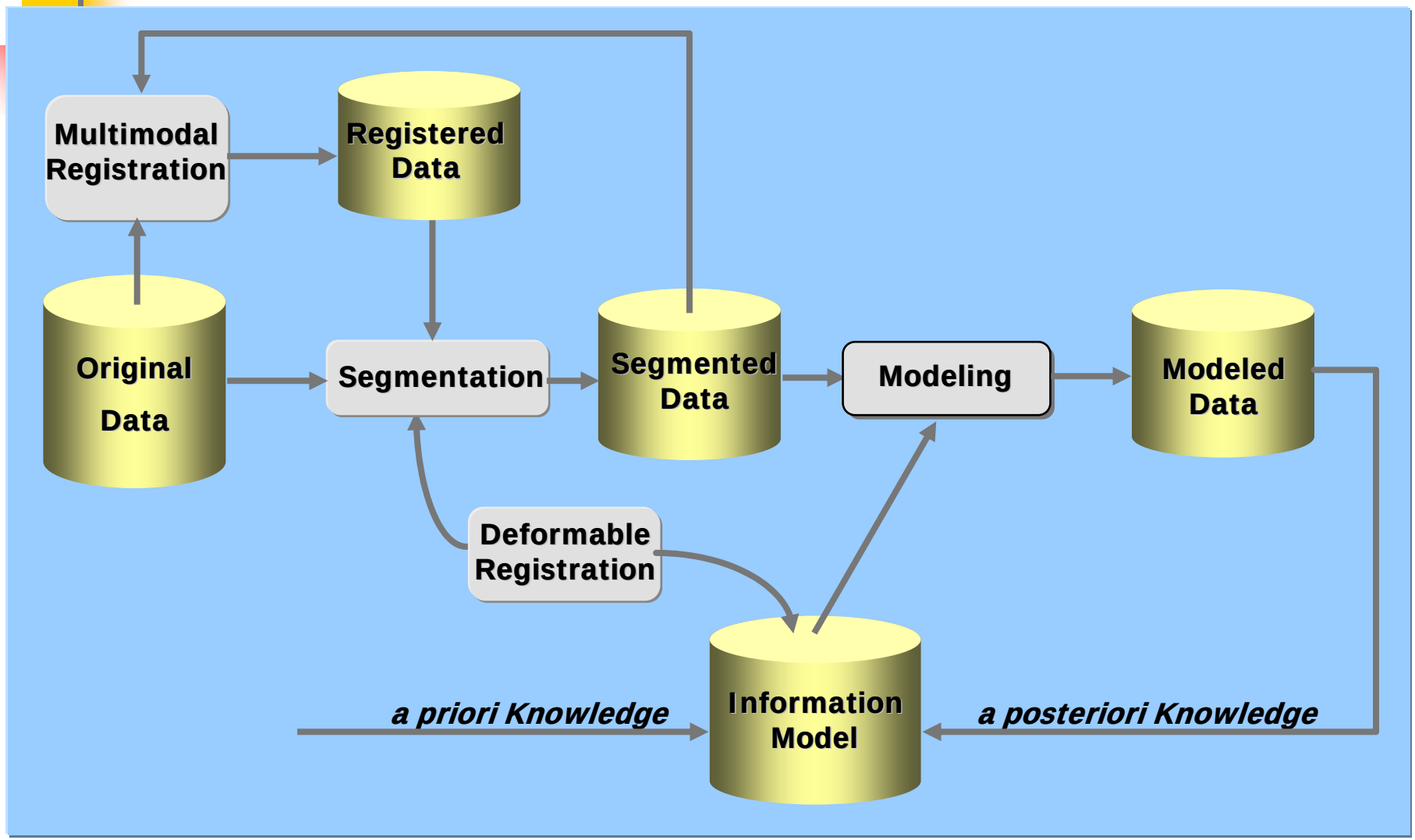
Evolution in Computer assisted surgery

Integration of new models and observations

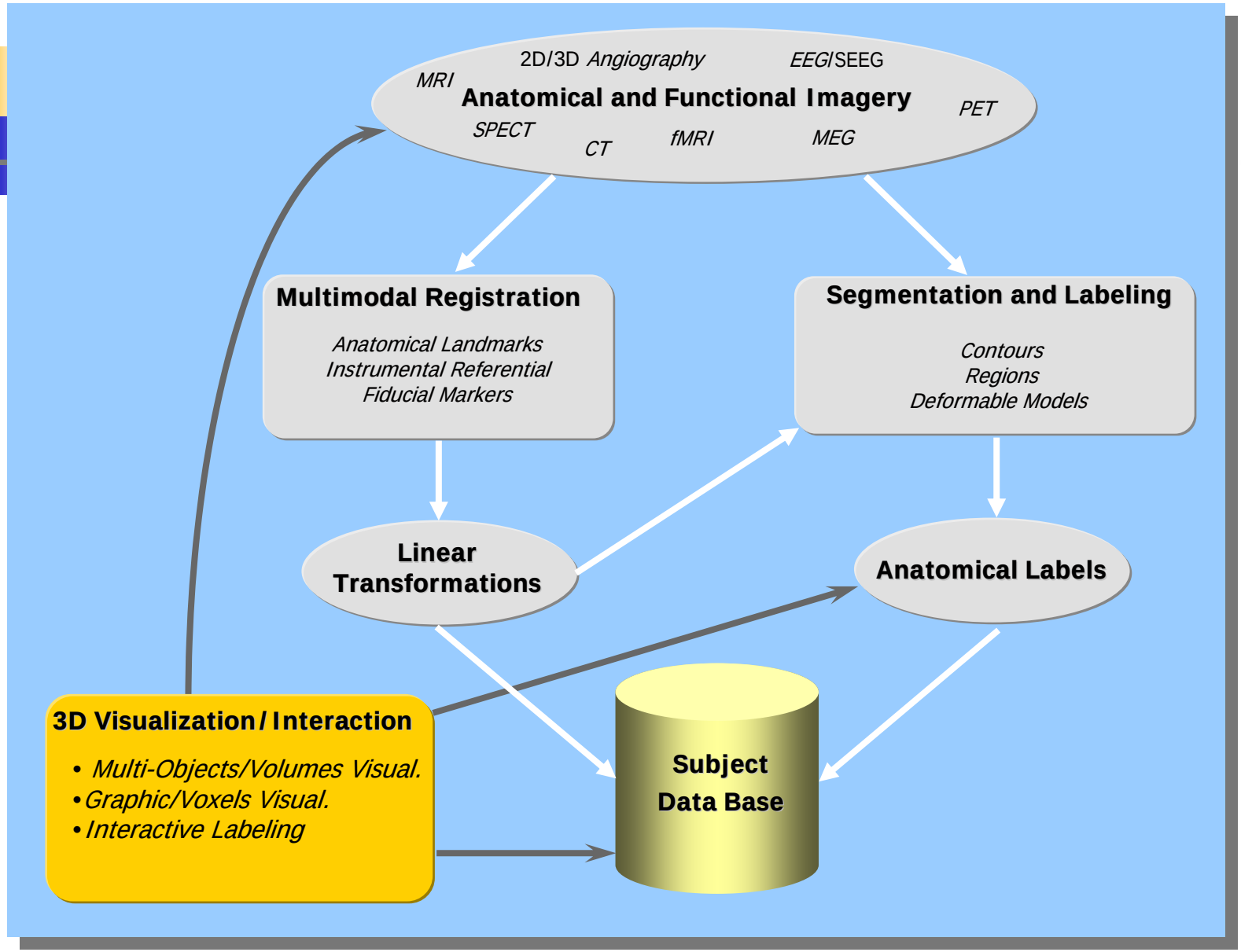
- Integration of new preoperative images (e.g. *DT-MRI*)
- Fusion between multimodal pre-operative images with intra-operative images to adapt the planning “in real time” for taking into account intra-operative deformations (*e.g. brain shift*)



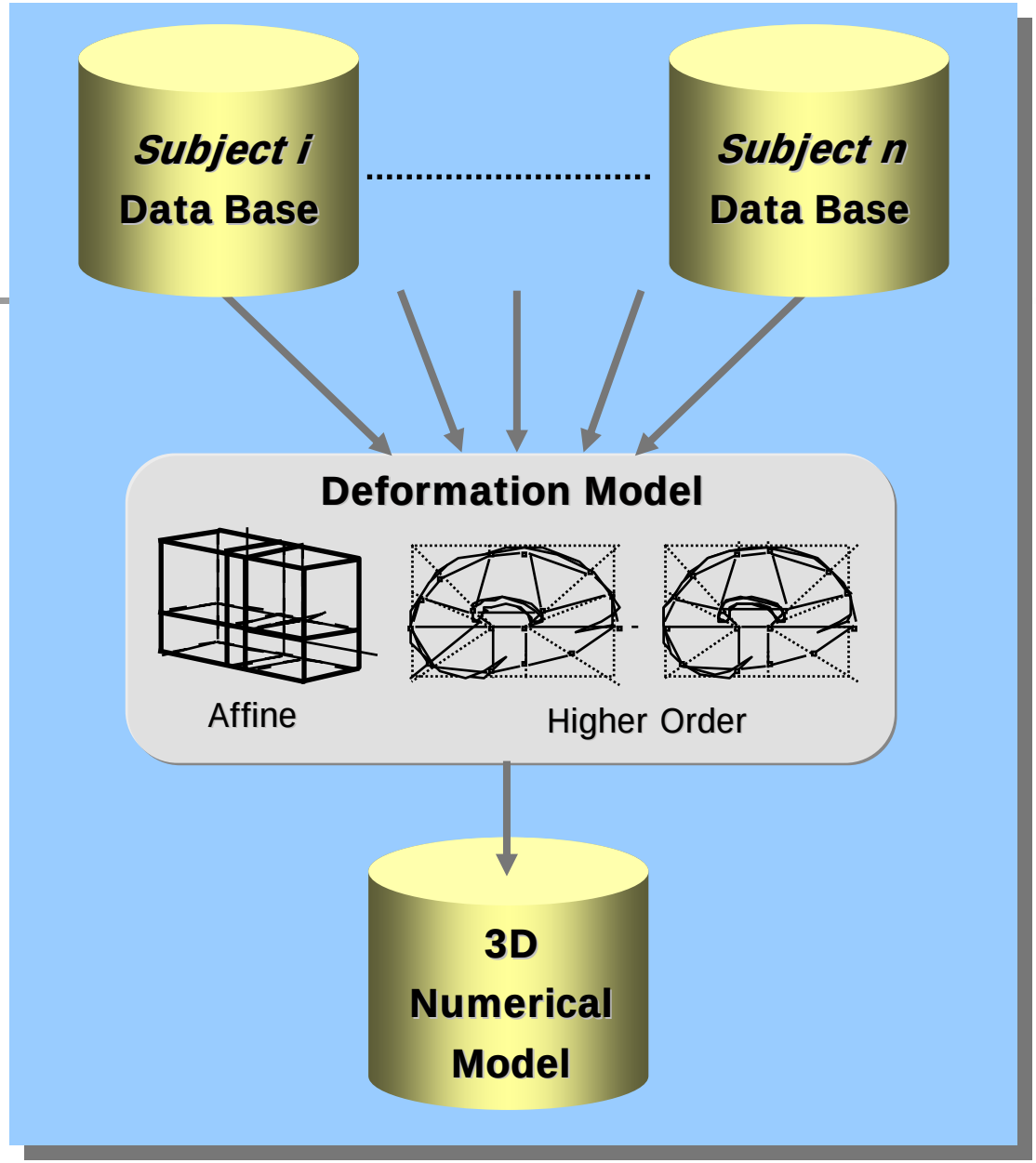
Cooperative Scheme for Data Fusion



Intra-Individual Data Fusion



Inter-Individual Fusion



Data Fusion in medical imaging

- What is Data Fusion?
  - Joint Use of Heterogeneous Data
- Why?
  - Co-exploitation of multimodal data
  - Registration / Matching
- Which Context ?
  - Computer assisted image interpretation systems

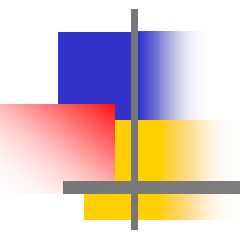
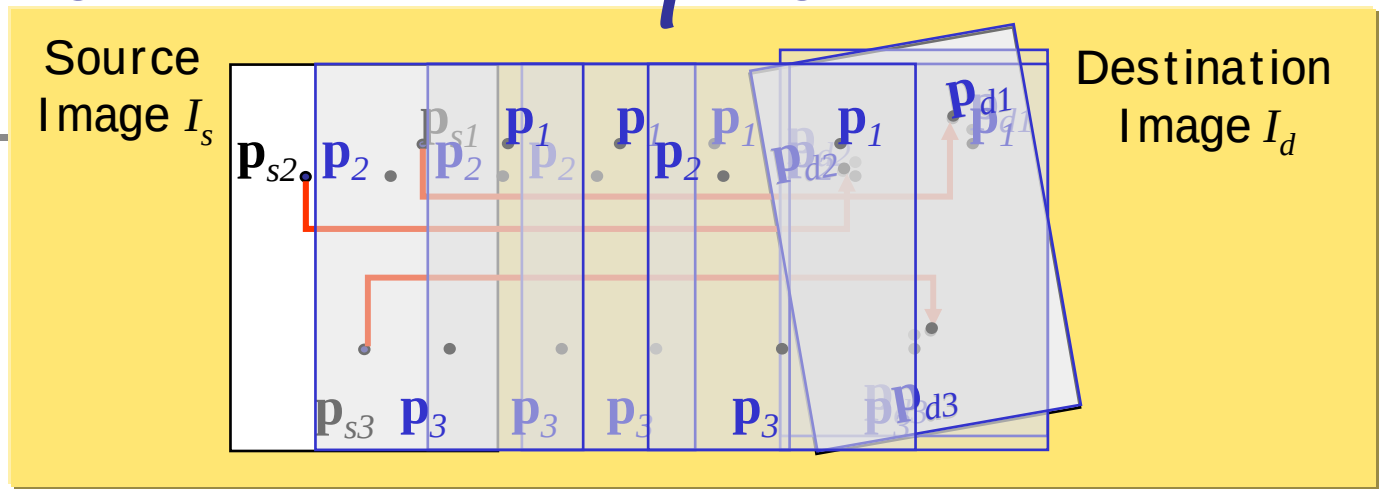


Image Registration

Basic concepts

Image Registration : *Basic Concepts*



- The notion of registration is to:

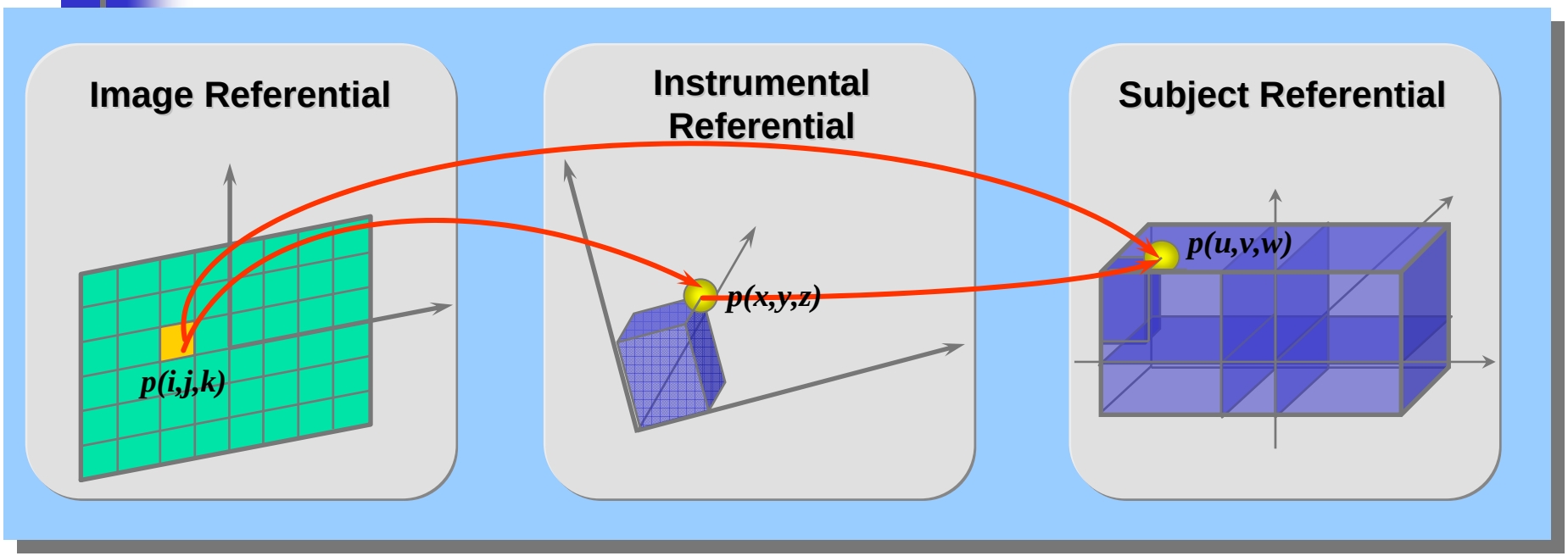
  Find a matching between points in one space (an image) **and points in another space** (also called a referential).

Problem: Find a Transformation Φ

Such as $I_s \xrightarrow{\Phi} I_d$

$\Phi = f(\mathbf{R}, \mathbf{T}, \delta(\mathbf{p}))$: $\Phi(\mathbf{p}_s) - \mathbf{p} = \varepsilon \rightarrow$ Optimization

Basic Referential



Class of registration domains

	ONE patient	SEVERAL patients
ONE modality	Intra-modality registration : - Post-operative control - Pathology tracking, Treatment probing	Intra-modality registration - Model-based segmentation - Registration/matching with an anatomical atlas - Spatial normalization, study of anatomical variability
SEVERAL modalities	Inter-modalities registration - Complementarities between sources of images - Computer assisted therapeutic planning - Computer assisted surgery - Anatomy-function correlation	Inter-modalities registration - Human brain mapping - Anatomo-functional normalization

Medical Image Registration : *Basic Concepts*

Definition: Let I_s and I_t be two images (*source* and *target*) to match, Ω_s and Ω_t, two homologous structures extracted from these images. The registration procedure consists in finding the transformation $\Phi : \Omega_s \rightarrow \Omega_t$ which registers a landmark ω in Ω_s to its correspondent $\Phi(\omega)$ in Ω_t.

- By generalization, this transformation can be applied to the underlying images I_s and I_t : $(I_t(x_1, y_1, z_1) = \Phi[I_s(x_2, y_2, z_2)])$
- For a given optimization method Ψ, the transformation $\Phi_{\theta \in \Theta}$ is computed by the optimization of :

$$\underset{(\theta \in \Theta | \Psi)}{argmin} \; \Delta\left(\Phi_\theta(\Omega_s) - \Omega_t\right)$$

where Δ is the similarity measure and $(\theta \in \Theta)$ the transformation parameters

Registration : The 4 basic stages

- Definition of homologous structures (Ω)
- Definition of the type of transformation (Φ)
- Definition of the cost function (Δ)
- Definition of the cost function optimization algorithm (Ψ)

Types of Homologous Structures (Ω)

- Size of the manifold (D_h)
  - 0D : point ($\Omega = Constant$)
  - 1D : contour ($\Omega = f(u)$)
  - 2D : surface ($\Omega = f(u,v)$)
  - 3D : volume ($\Omega = f(u,v,w)$)
  - nD : hypersurface ($\Omega = f(u_1,\ldots,u_n)$)
- Size of the evolution (Euclidian) space (D_w)
  - 2D : surface, projection ($\Omega \in \boldsymbol{R}^2$)
  - 3D : discrete or continuous space ($\Omega \in \boldsymbol{R}^3$)
  - nD, nD+t : hypersurface, spatio-temporal (2D+t); ($\Omega \in \boldsymbol{R}^n$)

Nature of Homologous Structures (Ω)

- External Referential :
  - Fiducial markers
  - Surgical frames (e.g. stereotactic)
- Anatomical Referential :
  - Anatomical landmarks (reference structures)
  - Image (*iconic*) features (gray levels, gradients, curvatures, ...)
  - Segmented shape

Which Transformation (Φ) ?

- Linear Transforms :

$$\begin{bmatrix} \begin{bmatrix} r_{11}s_1 & r_{12} & r_{13} \\ r_{21} & r_{22}s_2 & r_{23} \\ r_{31} & r_{32} & r_{33}s_3 \end{bmatrix} & \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} \\ \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} & w \end{bmatrix}$$

  - Rigid Transformation (rotation + translation)
  - Affine Transformation (rigid + scale)
  - Projective Transformation ($\Omega_s \in \boldsymbol{R}^n \rightarrow \Omega_d \in \boldsymbol{R}^{n-i}$, $i>0$)

- Non-linear Transformation (dense):
  - δ: $\mathbf{p}_d = \mathbf{p}_s + \delta(\mathbf{p}_s)$

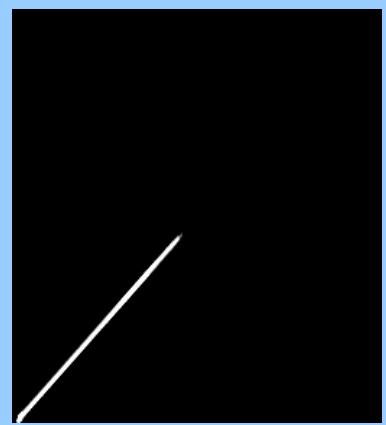
Similarity Function (Δ)

Definition: The similarity function defines the objective criteria (cost) used to estimate the quality of the registration between two homologous structures (Ω).

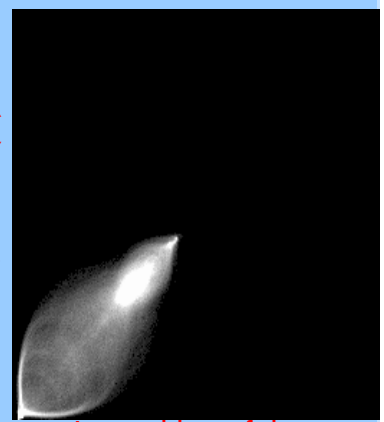
- Three big classes of measures:
  - Methods based on the definition of an intrinsic geometry (frame, external landmarks, reference planes, ...).
  - Methods based on Euclidian criteria (distances, surfaces, volumes).
  - Methods based on image intensities or their derivatives (correlation in the spatial or frequency domain, entropy, optical flow, ...)

Image registration: Measure from joint histogram

Joint Histogram
($HIST[x,y]$)

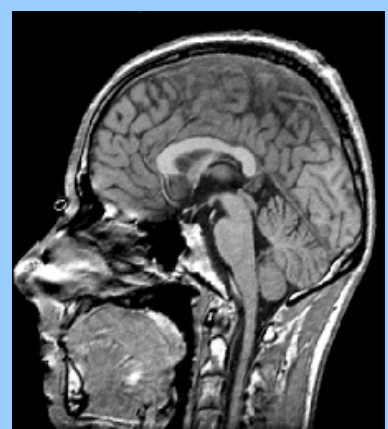


Intensities of the floating Image $Y=\Phi(X)$

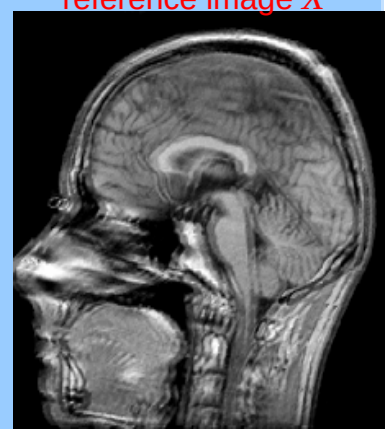


Intensities of the reference image X

Registered Images
($1/2*[X+\Phi(X)]$)

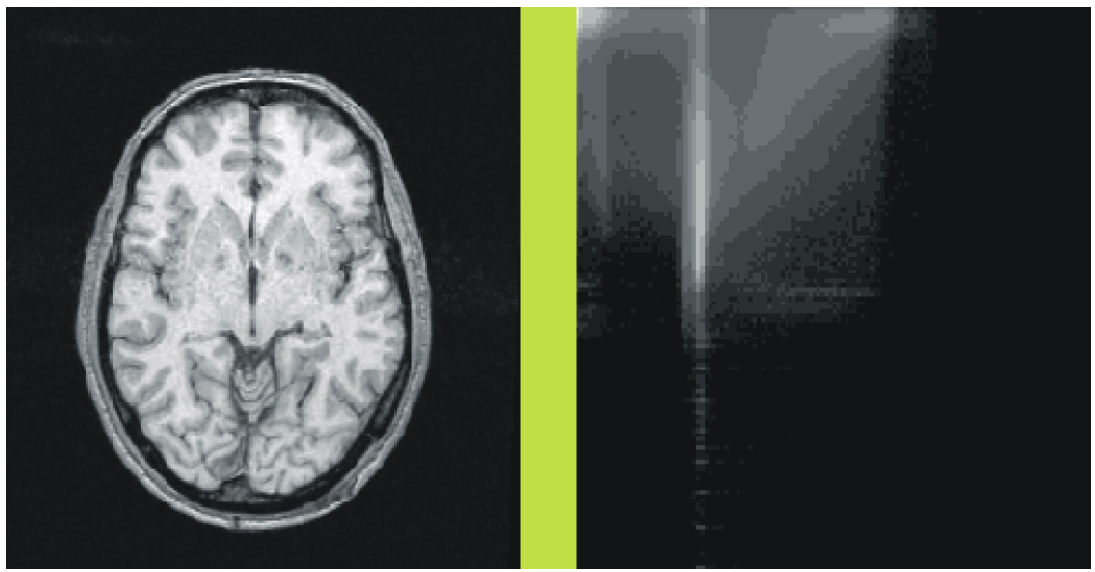


$\Phi=I$



$\Phi=T_x$

Image registration:
Relation between the transformation and the joint histogram

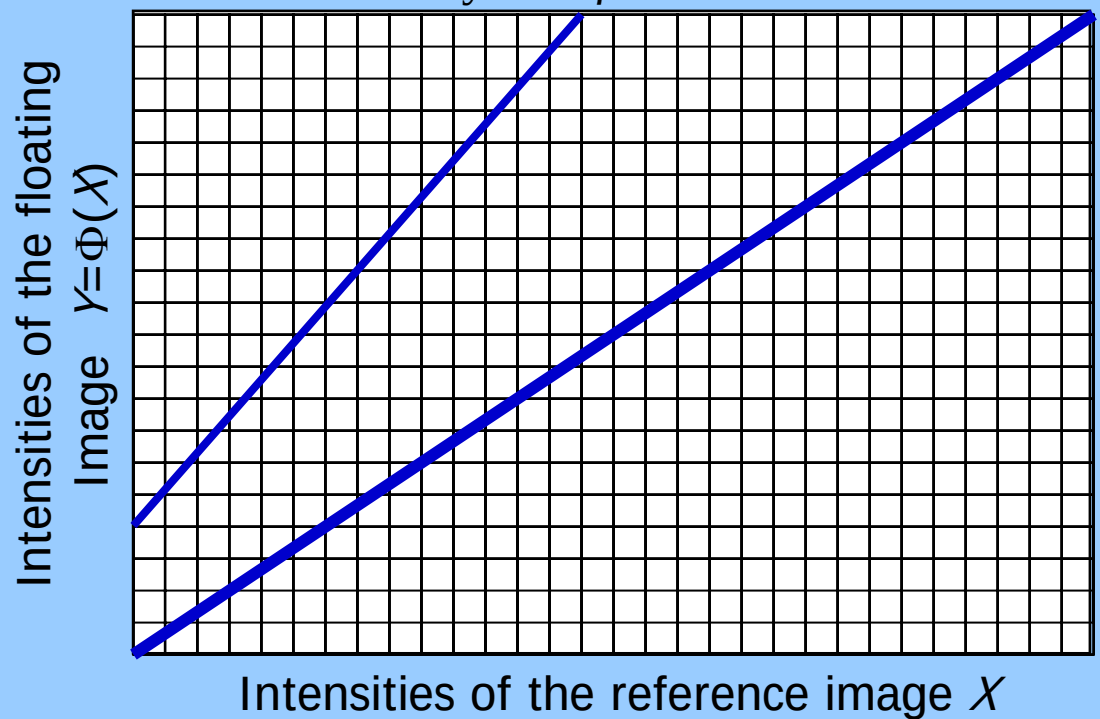


Joint Histogram: Linear or Affine Dependencies

Optimum $Corr(x,y)$

$y=\alpha x+\beta$

$$Corr(X,Y)=\frac{Cov(X,Y)}{\sqrt{\mathrm{var}(X).\mathrm{var}(Y)}}$$



Optimum SSD/SAD

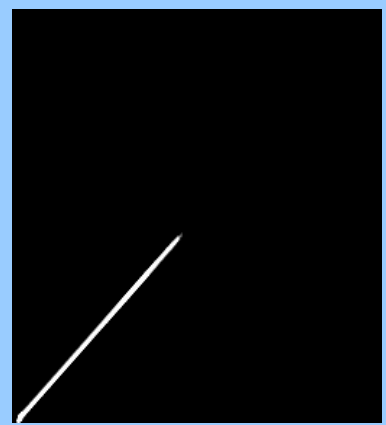
$y=x$

$$SSD(X,Y)=\sum_{x\in X,y\in Y}(x-y)^2$$

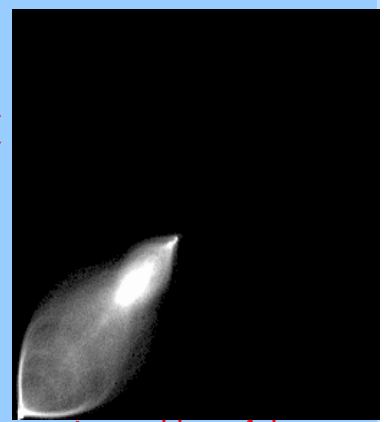
$$SAD(X,Y)=\sum_{x\in X,y\in Y}|x-y|$$

Joint Histogram:
Examples of Linear or Affine Dependencies

Joint Histogram
($HIST[x,y]$)

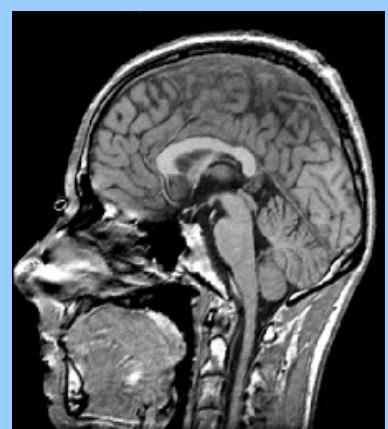


Intensities of the floating image $Y=\Phi(X)$

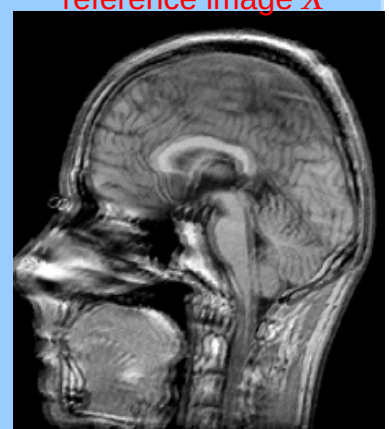


Intensities of the reference image X

Registered Images
($1/2*[X+\Phi(X)]$)

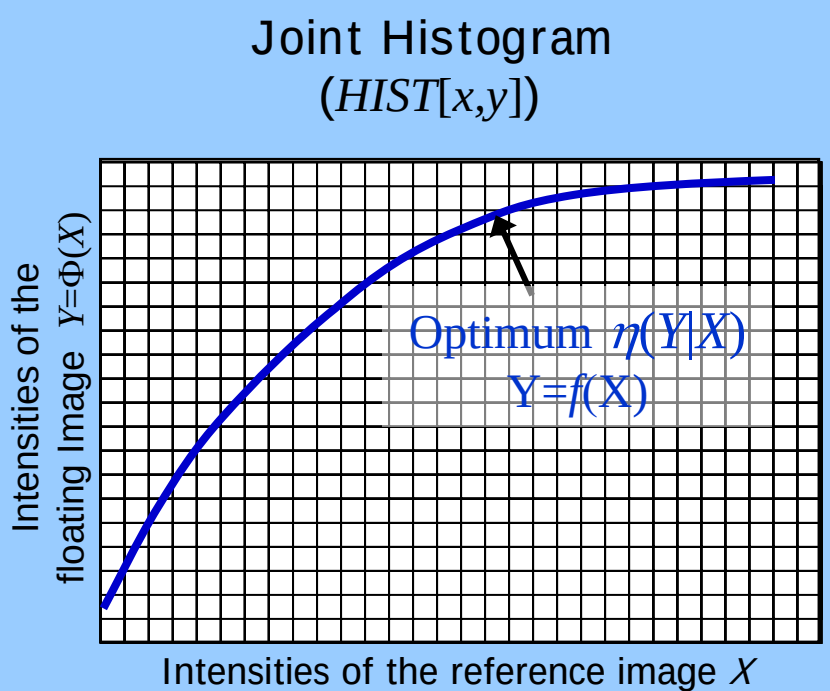


$\Phi=I$

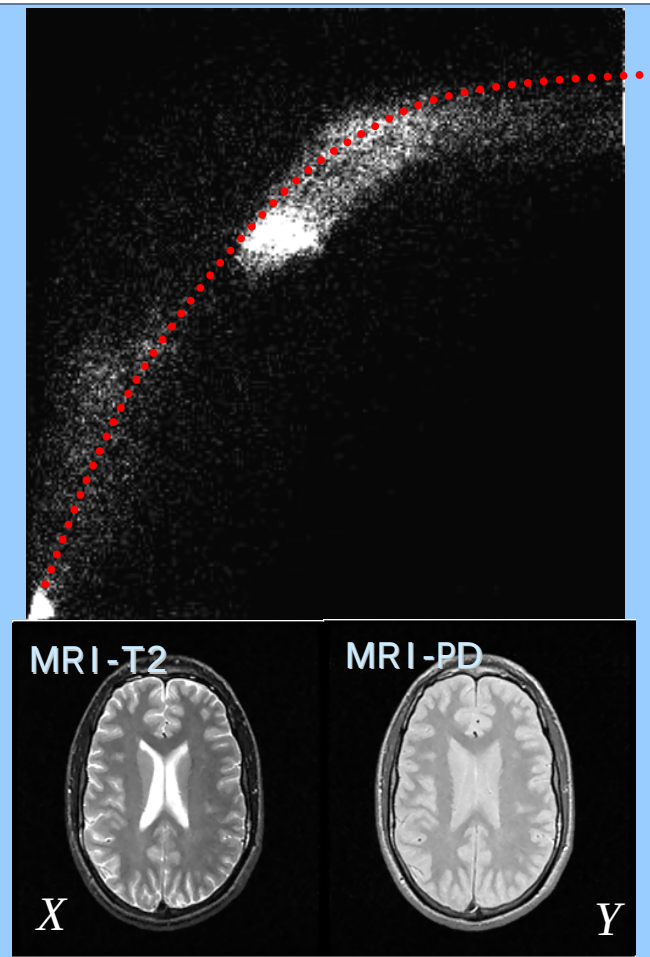


$\Phi=T_x$

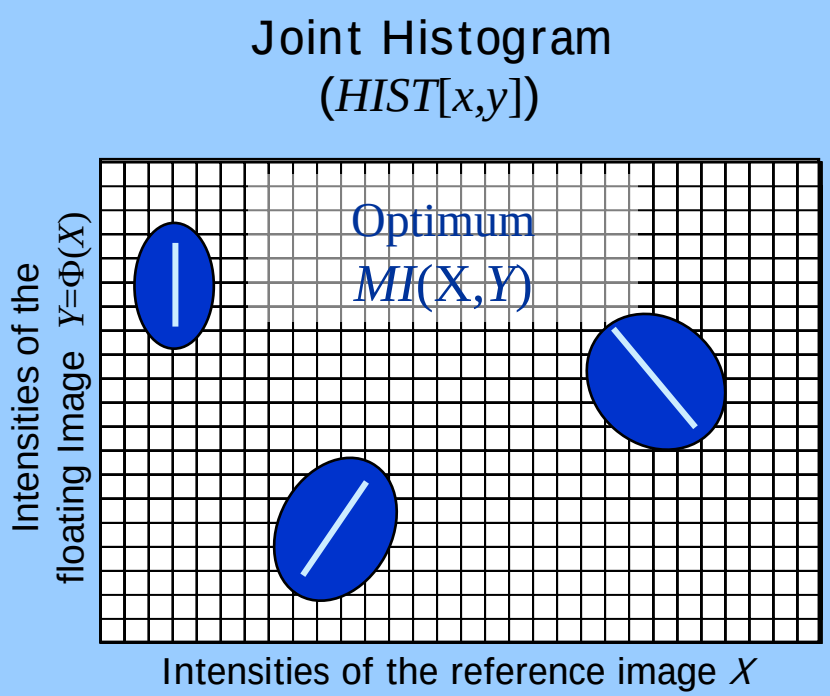
Joint Histogram:
Functional Dependencies (*e.g. Correlation Ratio*)



$$\eta(Y|X) = 1 - \frac{\mathrm{var}\left[Y - E(Y|X)\right]}{\mathrm{var}(Y)}$$

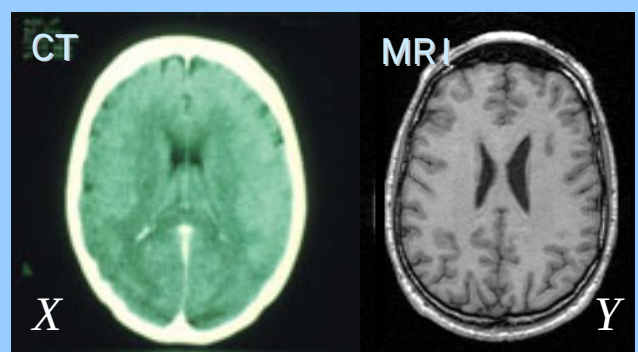


Joint Histogram:
Statistical Dependencies (*e.g. Mutual Information*)

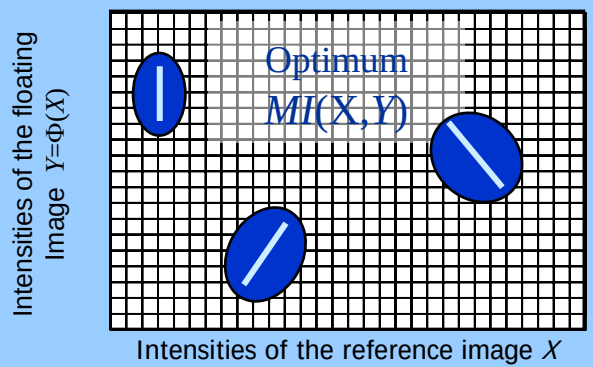


$$MI(X,Y) = H(X) + H(Y) - H(X,Y)$$

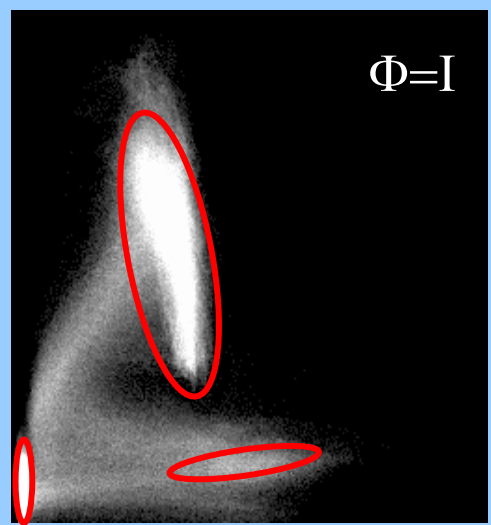
$$NMI(X,Y) = (H(X) + H(Y)) / H(X,Y)$$

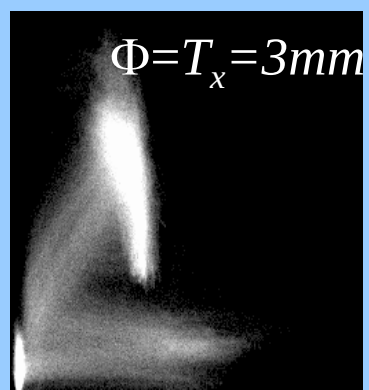


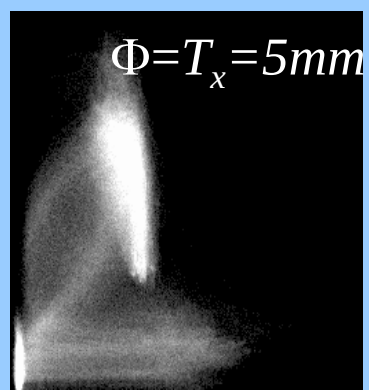
Joint Histogram:
Statistical Dependencies (*e.g. Mutual Information*)

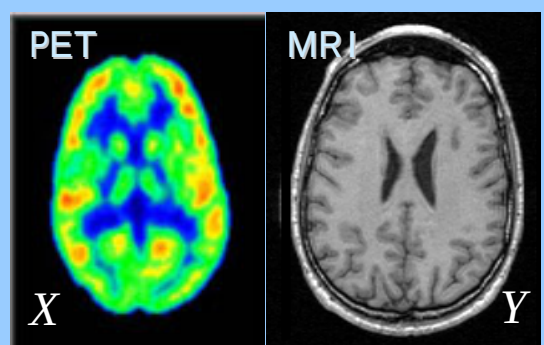


Joint Histogram
($HIST[x,y]$)



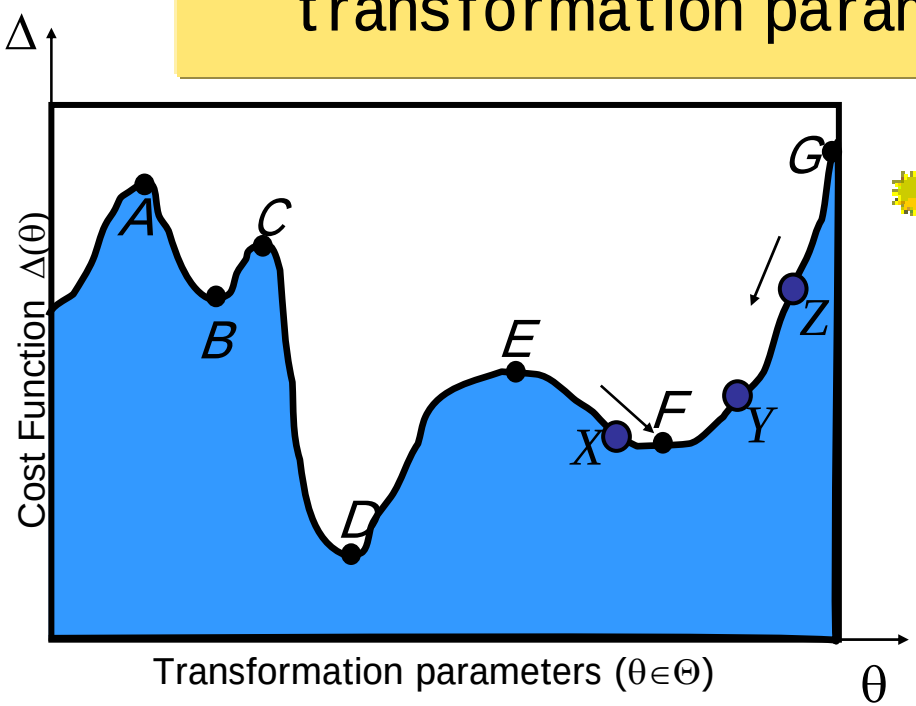






Optimization Issues (Ψ)

Definition: The optimization method defines how the cost function (Δ) will be minimized (or maximized) with respect to the set of transformation parameters $\theta \in \Theta$.



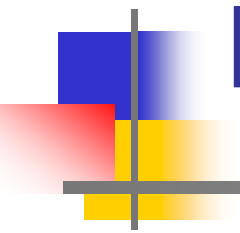
- Idea: the goal is to find the minimal value (i.e. *D* rather than *F*) of $\Delta(\theta)$ from any initialization point (e.g. *G*)

Optimization Methods (Ψ)

- Non Global optimization methods:
  - Quadratic or semi-quadratic approaches
  - May need the estimation of partial derivatives of $\Delta(\theta)$.
  - Assume a quasi-convex energy around the desired solution
  - Need a hierarchical resolution scheme (multiscale, multi-resolution)
  - Examples:
    - Least square, ICP, Gradient Descent, Newton-Raphson, Levenberg-Marquardt, Simplex, Powell...

Optimization Methods (Ψ) *(2)*

- Global optimization methods:
  - More robust approaches (proof of convergence at an infinite state)
  - Computational cost
  - Non applicable to high dimensional problems (*e.g. iconic registration*)
  - Examples:
    - Dynamic Programming, Simulated Annealing, Genetic Algorithms, Clustering Methods, Branch and Bound, Evolutionary Algorithms, Statistical Methods , ...



Deformable Registration

Deformable Registration: Not a new topic!

- Classical topic in morphometry (e.g. [D'Arcy Thomson, 1917])

(Source: D'Arcy Thomson, *On Growth and Form*, Cambridge University Press, 1961)

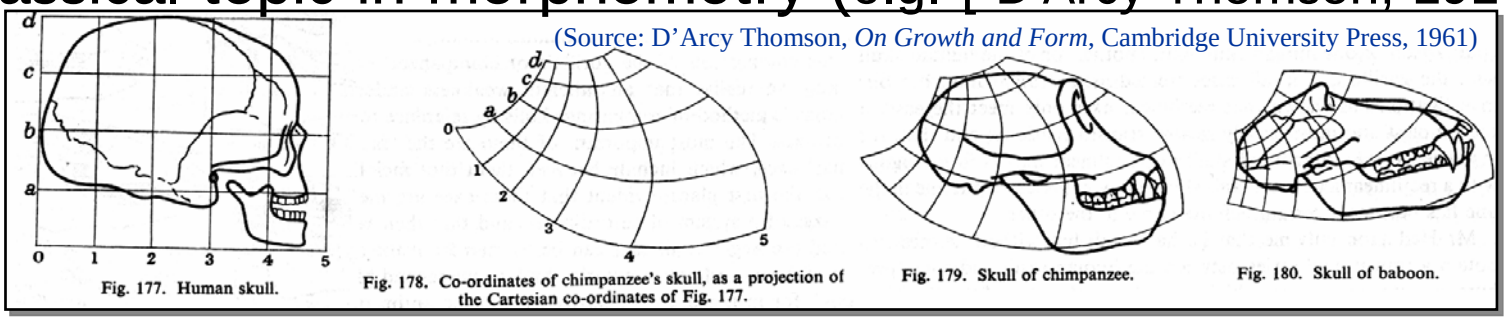


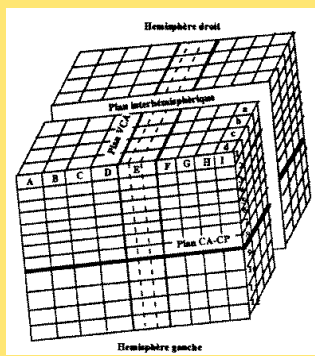
Fig. 177. Human skull.

Fig. 178. Co-ordinates of chimpanzee's skull, as a projection of the Cartesian co-ordinates of Fig. 177.

Fig. 179. Skull of chimpanzee.

Fig. 180. Skull of baboon.

- Classical topic for brain imaging (e.g. [Talairach et al., 1967])



(Source: J. Talairach, G. Szikla, P. Tournoux, A. Prosalentis, and M. Bornas-Ferrier, *Atlas d'Anatomie Stéréotaxique du Télencéphale*. Masson, Paris, 1967)

- Introduction of computer based procedures in the 80's (R. Bacjsy, C. Broit and coll.; U. Grenander and coll.; F. Bookstein, ...)

Deformable Registration: evolution in a decade*

In IPMI (*oral*):

[86-88] F. Bookstein (*general morphometry, brain, TPS*)

[91] F. Bookstein (*general morphometry, brain, TPS*)
D. Lemoine *et al.* (*brain, Talairach Grid System*)

[93] F. Bookstein *et al.* (*general morphometry, brain, TPS*)
K. Shields *et al.* (*carotid plaques in US*)

[95] G. Christensen *et al.* (*brain, fluid model*)
L. Collins *et al.* (*brain, atlas based segmentation*)
J. Gee *et al.* (*brain, bayesian framework)*
S. Sandor *et al.* (*brain*, *atlas based segmentation*)

[97] P. Edwards *et al.* (*brain, interventional imaging*)
T. Schiemann et al. (*volume interaction*)

[99] A. Caunce *et al.* (*sulci shape model*)
G. Christensen *et al.* (*brain, homomorphism*)
H. Chui *et al.* (*brain cortical point*)
L. Collins *et al.* (*brain, atlas based segmentation*)
H. Lester *et al.* (*brain, fluid model*)
D. Rey *et al.* (*brain, growth of pathologies*)
K. Rohr et al. (*TPS*)
O. Skrinjar *et al.* (*brain, interventional imaging*)
M. Vaillant *et al.* (*brain cortical surface*)

** data collected from IPMI (Information Processing in Medical Imaging)*

Deformable registration: When?

	ONE patient	SEVERAL patients

ONE modality	■ Registration of temporal sequences :
	  ■ Temporal deformation of anatomical structures (heart, chest, blood flow)
	  ■ Growth, Pathologies follow-up
		■ Model-based segmentation
		■ Building of digital atlases
		■ Registration/matching with an anatomical atlas
		■ Spatial normalization, study of anatomical variability

SEVERAL modalities	■ Correction of fMRI acquisitions ■ Constraints to reconstruction / restoration algorithms ■ Computer Assisted Surgery ■ registration between pre- and intra-operative images (e.g. MRI and Ultrasound)	■ Human brain mapping ■ Anatomo-functional normalization (aid for the study of functional variability)

Deformable Registration : which transformation?

- Non-linear dense transformation:

Definition : The transformation can be represented as a dense deformation field: a displacement vector δ is associated to each point of the homologous structures Ω_s and Ω_t :

$$\delta: p_t = p_s + \delta(p_s)$$

- In an energetic framework, the general formulation becomes:

$$\underset{(\theta \in \Theta | \Psi)}{argmin} \; E\left[\Delta\left(p_s + \delta_\theta(p_s), p_t\right)\right] + E\left[\delta_\theta\right]$$

In a Bayesian context: Likelihood : $p((p_s, p_t)|\delta)$ Prior : $p(\delta)$

Continuity of the transformation ($E[\delta_\theta]$)

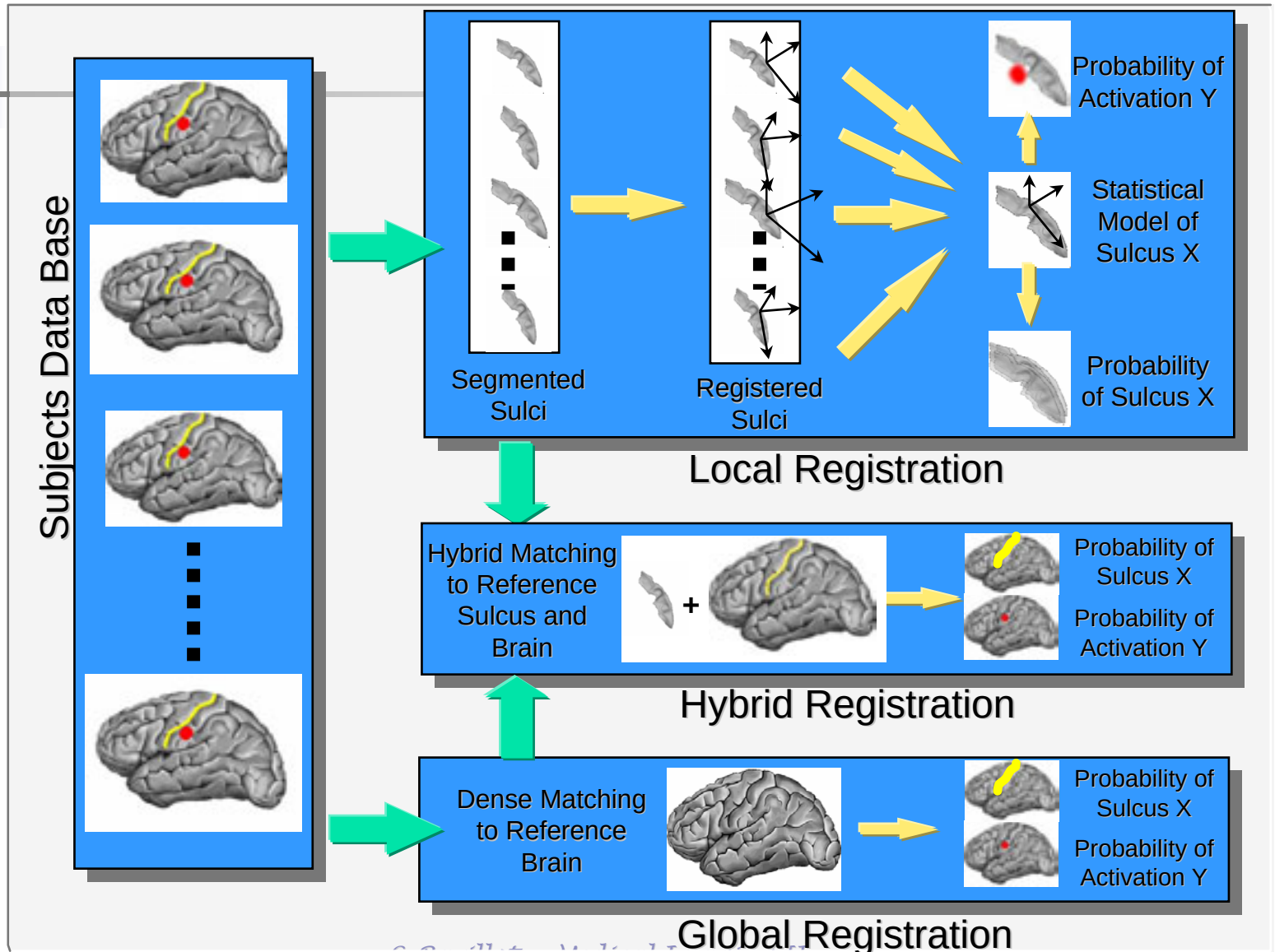
- Piecewise linear (C^0 continuity) (e.g. Talairach)
- Splines (C^1, C^2 continuity) (e.g. RBF, Free-form deformation)
- Mechanical Models :
  - Linear elasticity models (Navier equations)
  - Fluid models (Navier-Stokes equations)

Defomable Registration: Local and Global approaches

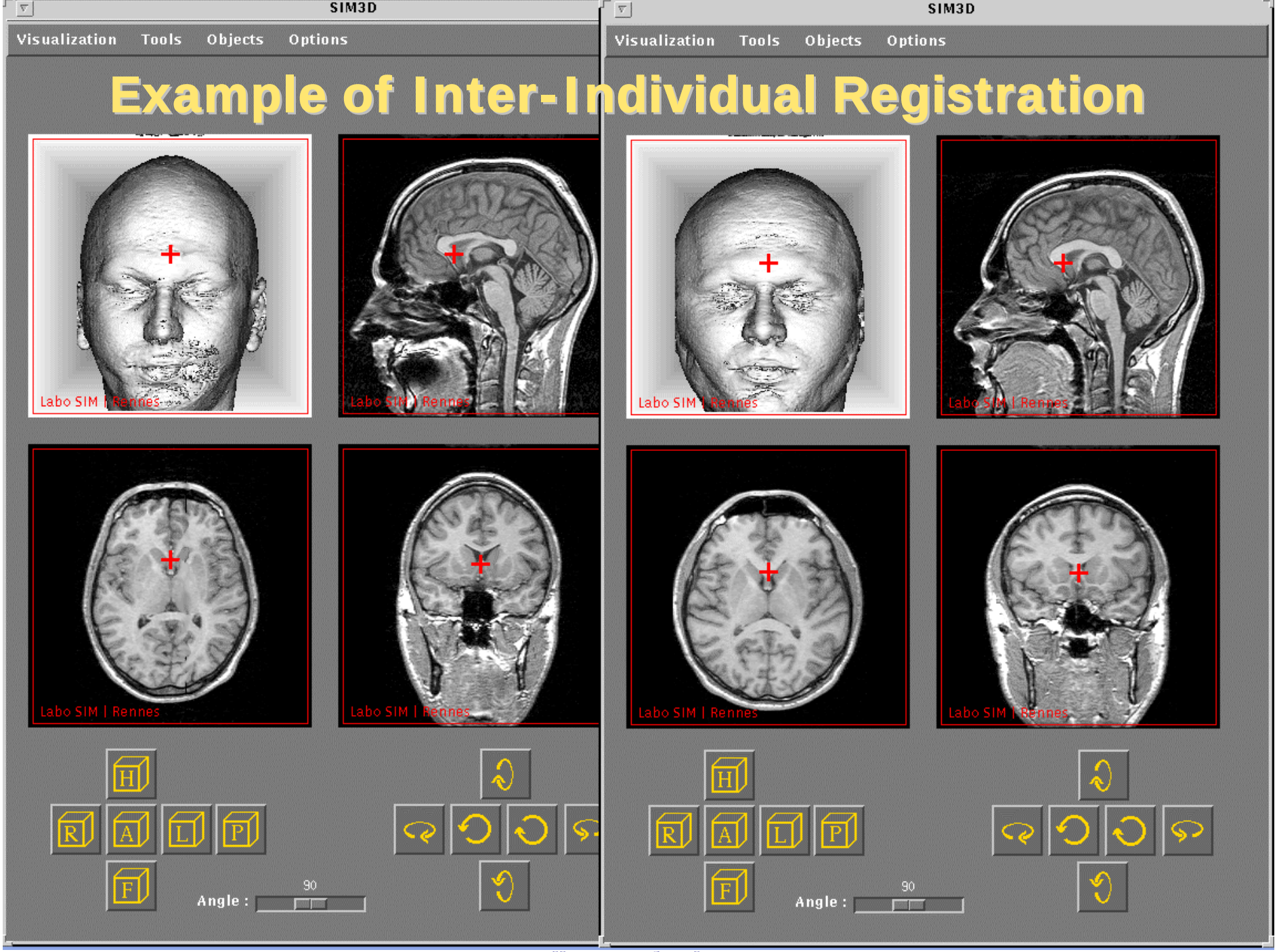
- Global, or “photometric” methods $(D_h = D_w)$
  - Rely on photometric similarity measures
  - Provide a dense deformation field
  - Anatomical coherence of the transformation?
  - High dimensional optimization problem
- Local, or “geometric” methods $(D_h < D_w)$
  - Rely on extracted features (point, curves, surfaces)
  - Interpolation necessary (e.g. thin-plate-spline, RBF, ...)
  - The transformation is mostly relevant in the neighborhood of the homologous features

➢ *Hybrid: use of both homologous structures*

Image fusion in neuroimaging using Global, Local and Hybrid methods



Example of Inter-Individual Registration



Deformable Registration: Local, or "geometric" methods

Definition of local landmarks

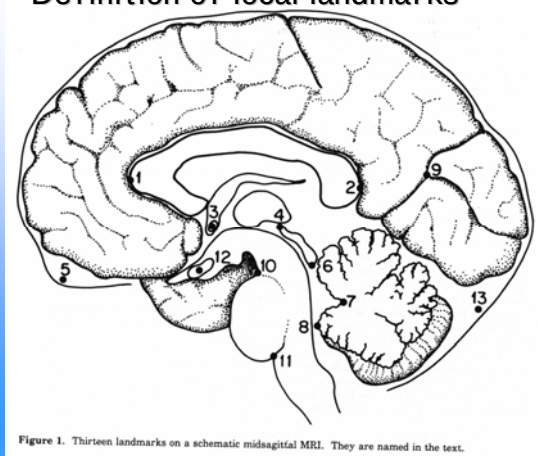
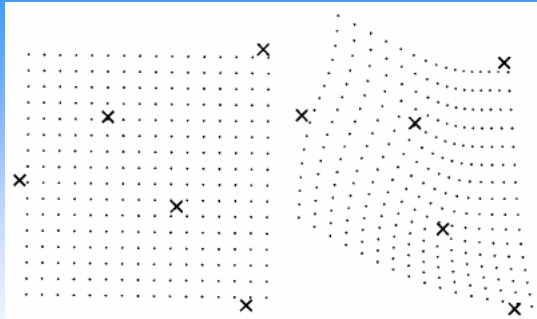
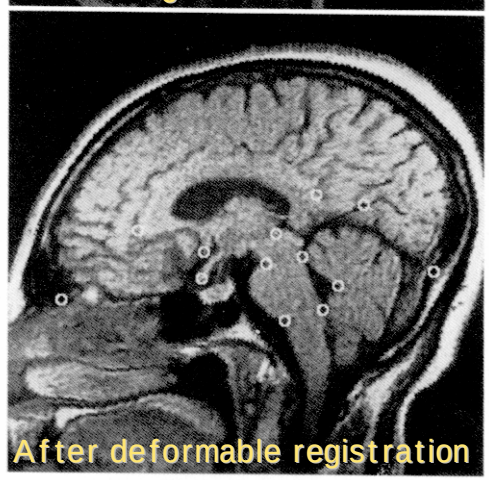


Figure 1. Thirteen landmarks on a schematic midsagittal MRI. They are named in the text.

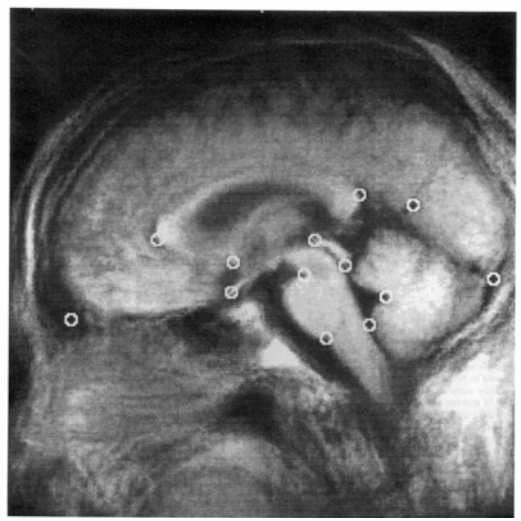


Definition of a deformation model

Before registration



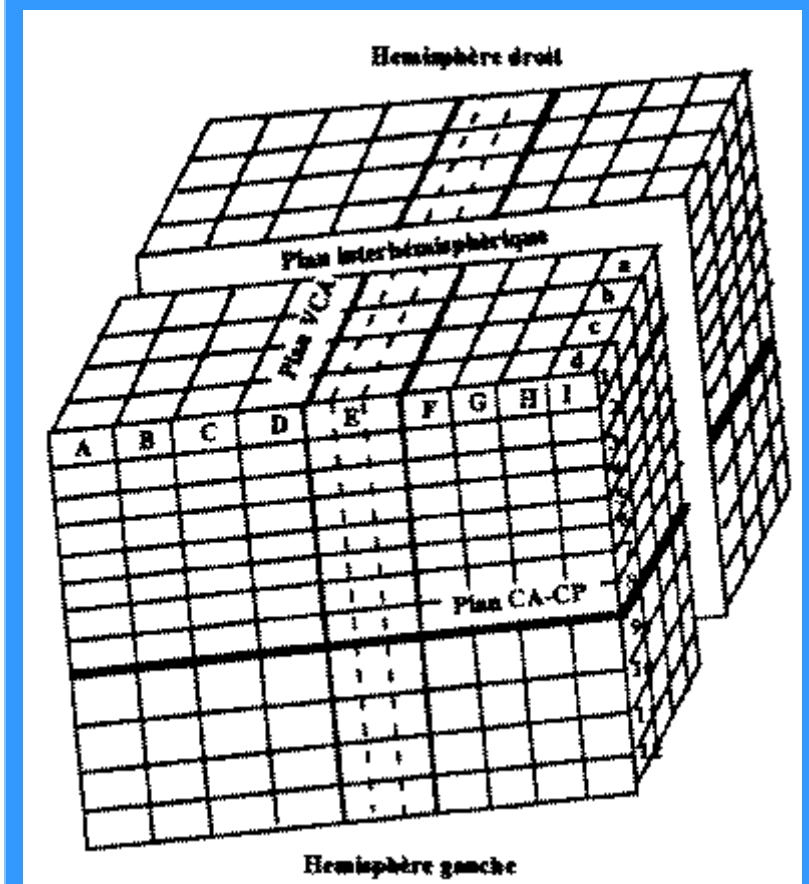
After deformable registration

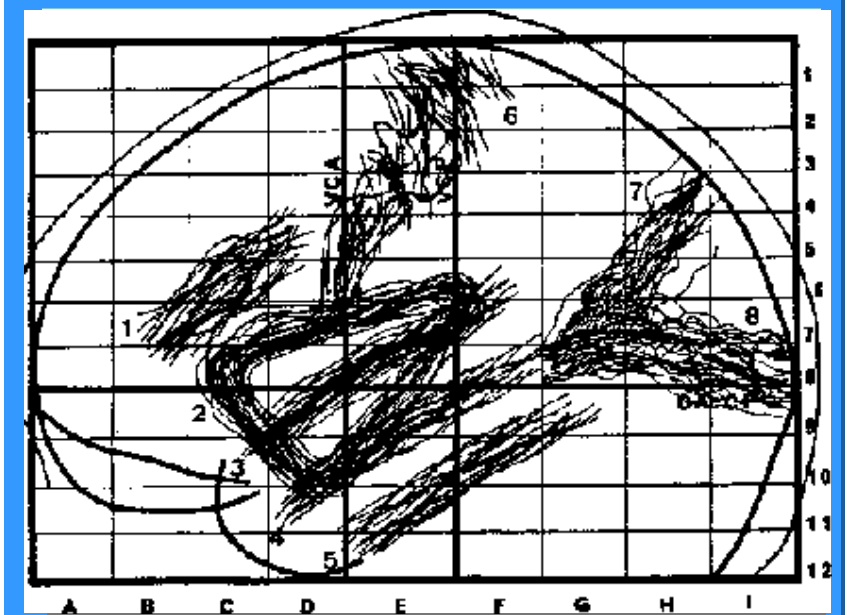


Averaging of 9 brains

(Source: F. L. Bookstein, *Thin-plate splins and the atlas problem for biomedical images*, IPMI, Wye College, UK, 1991)

Talairach Stereotactic Proportional Grid System

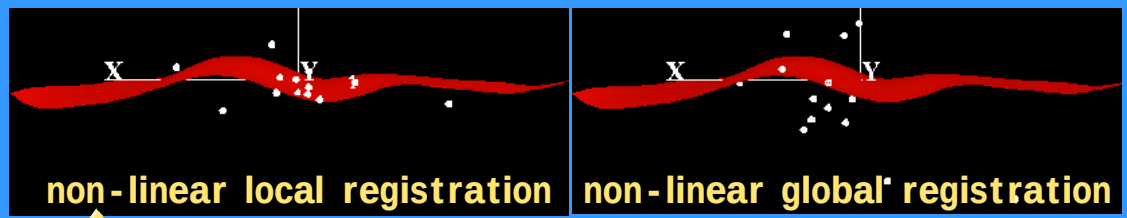




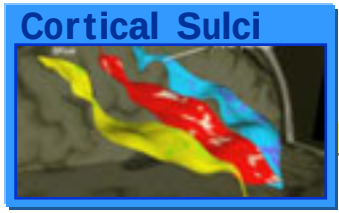
(Source: J. Talairach, G. Szikla, P. Tournoux, A. Prosalentis, and M. Bornas-Ferrier, *Atlas d'Anatomie Stéréotaxique du Télencéphale*, Masson, Paris, 1967)

Probabilistic atlas based on local constraints

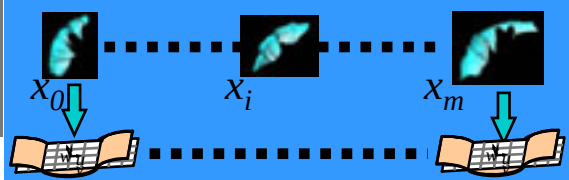
Inter-subjects registration of sparse data (MEG)



Cortical Sulci



local referential



Constraints on TPS

$$f(x,y,z) = a_0 + a_1x + a_2y + a_3z + \sum_{i=1}^{m} w_i U(|P_i - (x,y,z)|), U(r) = r^2 \log r^2$$

Statistical Shape Analysis

$$\overline{X} = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$C = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i \tilde{x}_i^T ; \tilde{x}_i = x_i - \overline{X}$$

$$C = \Phi \Lambda \Phi^T ; \Lambda = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_m \end{bmatrix}$$

Analysis

Reconstructed Sulcus

Sulcus Mean Shape

Modal Amplitudes

Modes Matrix

$$x = \overline{X} + \Phi b$$

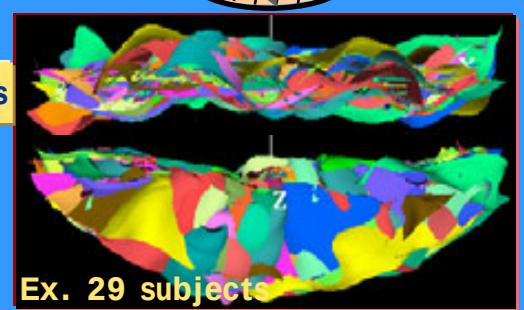
Synthesis

$$x \approx \overline{X} + \sum_{i=1}^{m} \phi_i b_i$$

$$x = \overline{X} + \phi_1 b_1$$

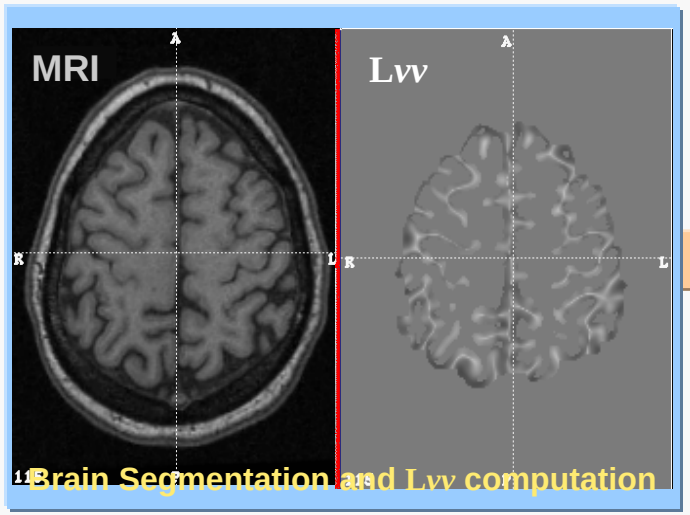
$$b_1 \in \left[-2\sqrt{\lambda_1}, +2\sqrt{\lambda_1}\right]$$

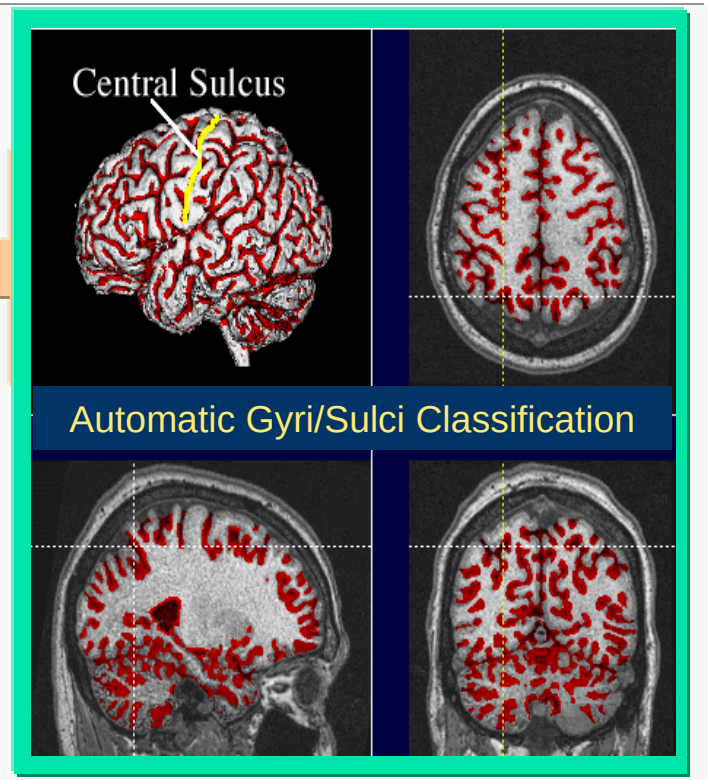
Modal Analysis

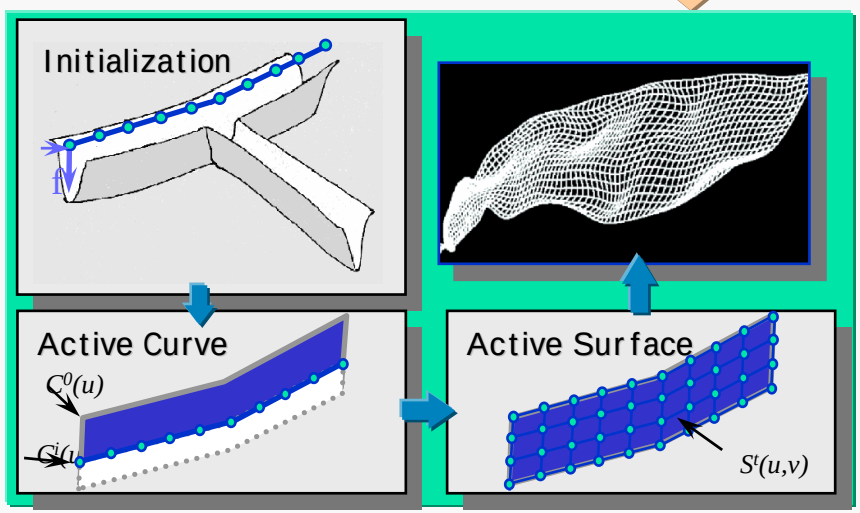


Registration and matching

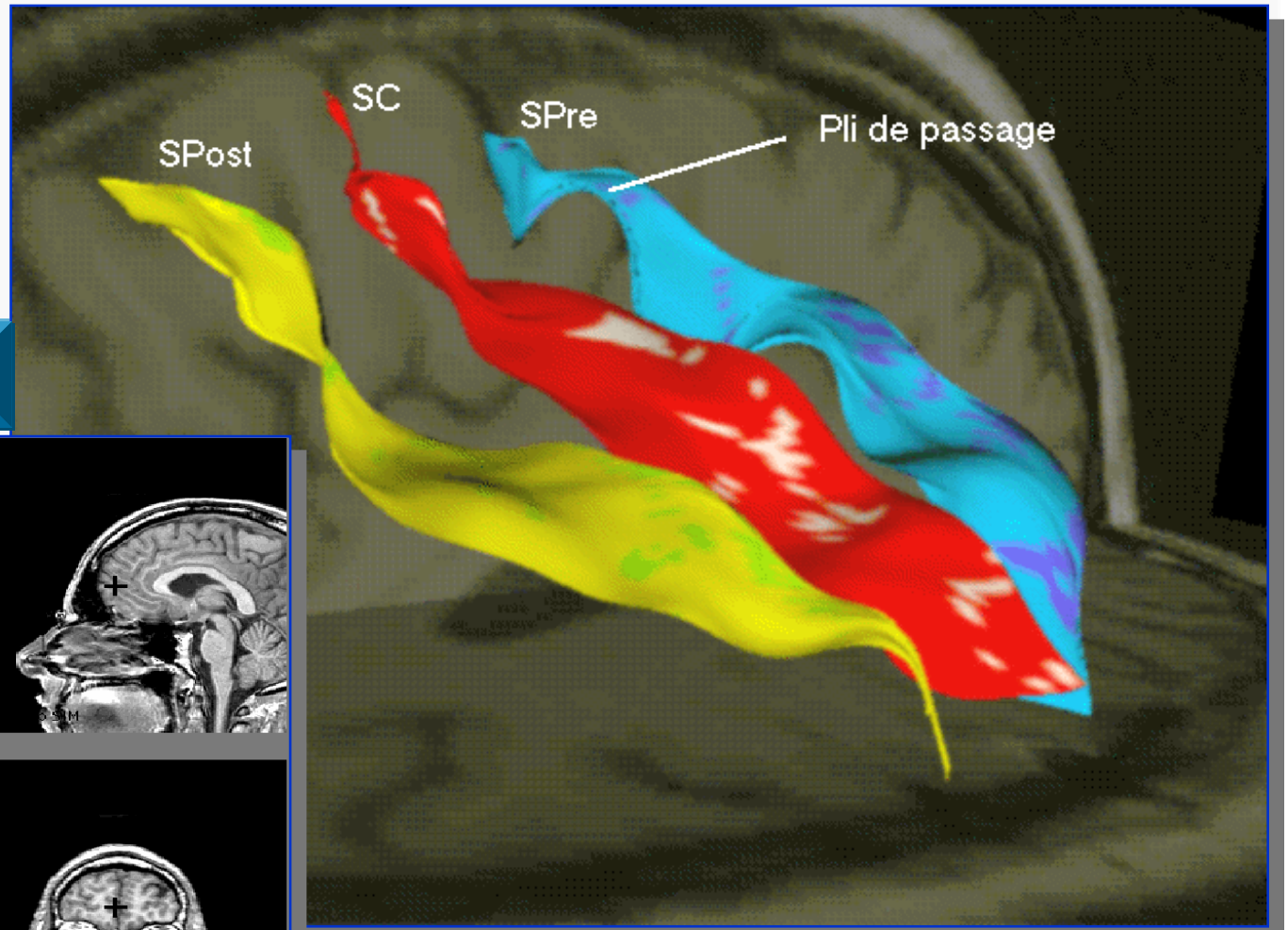
Segmentation of the sulci using the «Active Ribbon» Method

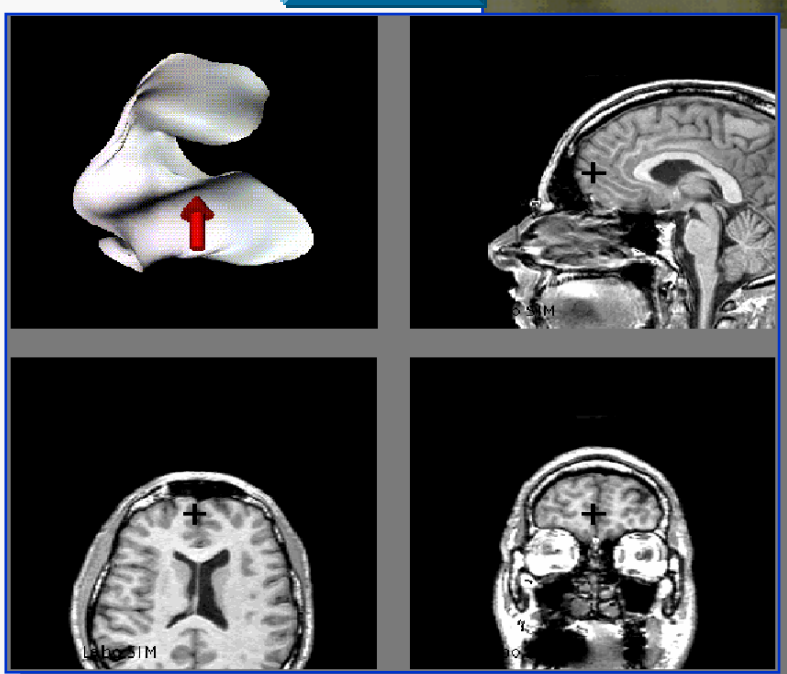




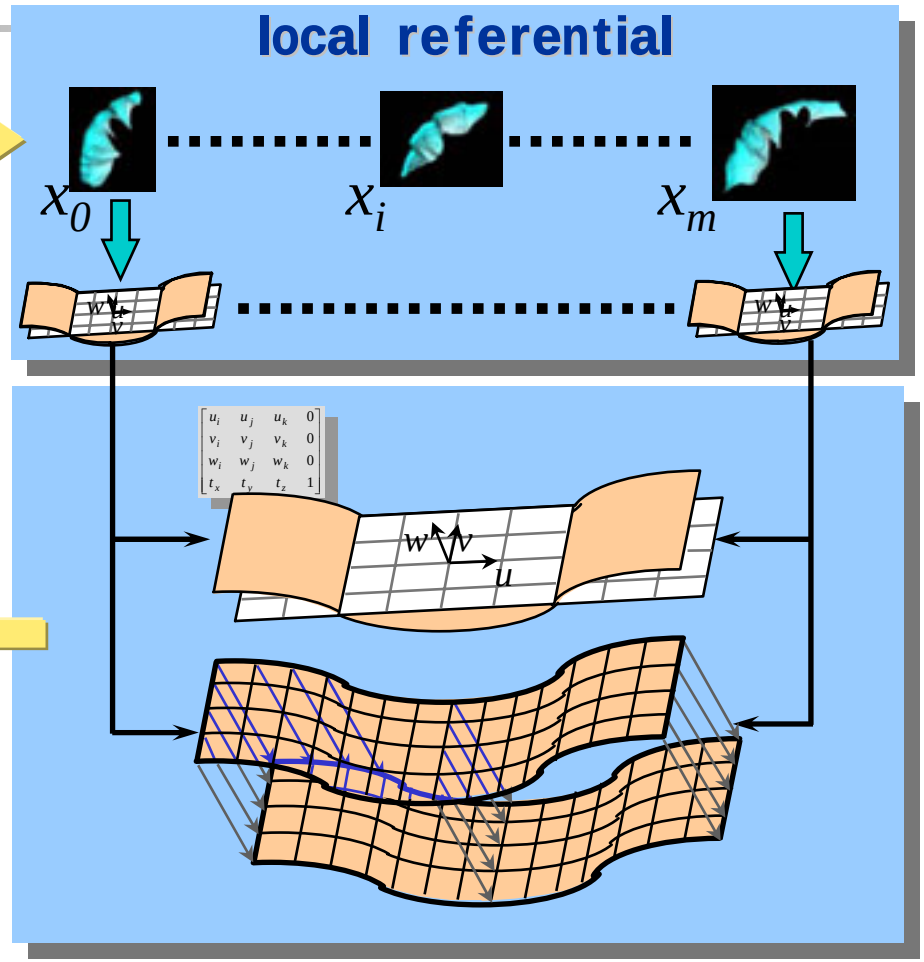


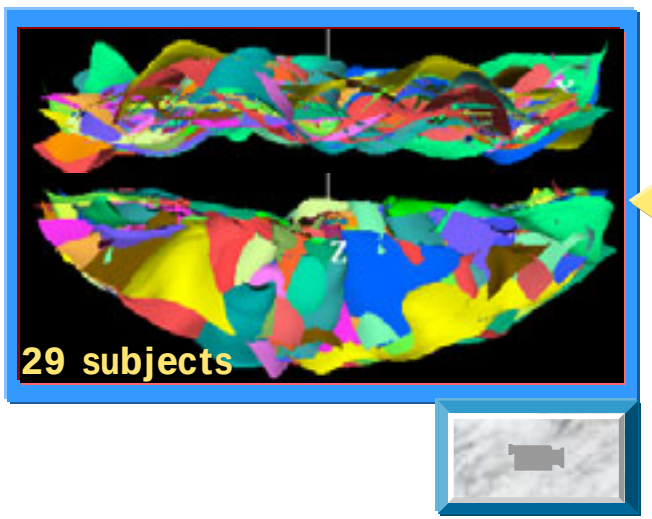
Extraction of the local features



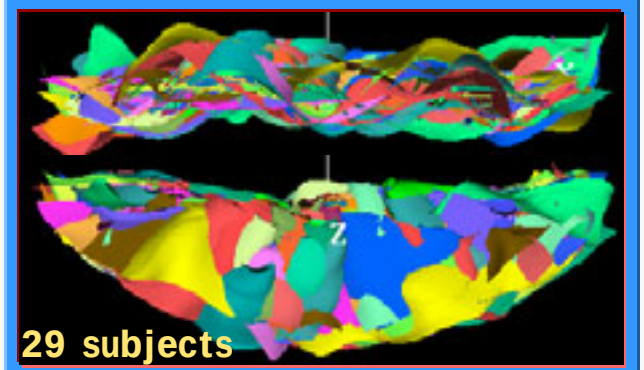


Linear Local Registration (*LR*)





Statistical Shape Model : Principal Component Analysis



$$\overline{X} = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$C = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i \tilde{x}_i^{\,T} \; ; \; \tilde{x}_i = x_i - \overline{X}$$

$$C = \Phi \Lambda \Phi^{T} \; ; \; \Lambda = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_m \end{bmatrix}$$

Analysis

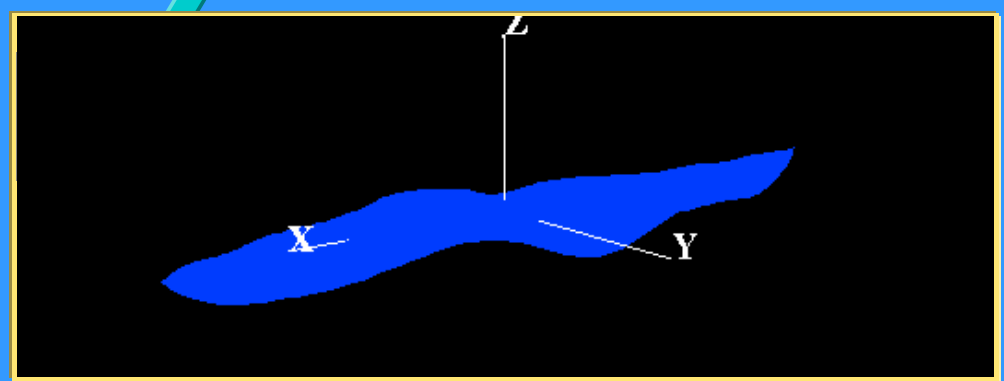
Mean Shape

Reconstructed Shape

Modal Amplitudes

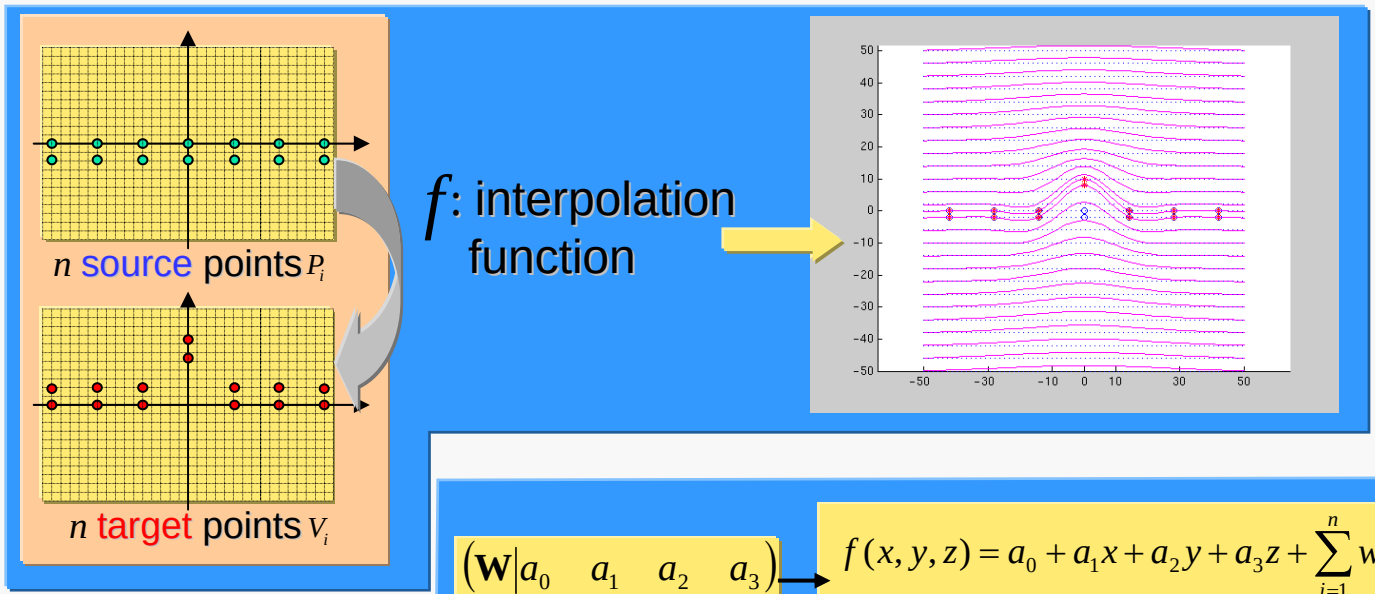
Modes Matrix

$$x = \overline{X} + \Phi b$$

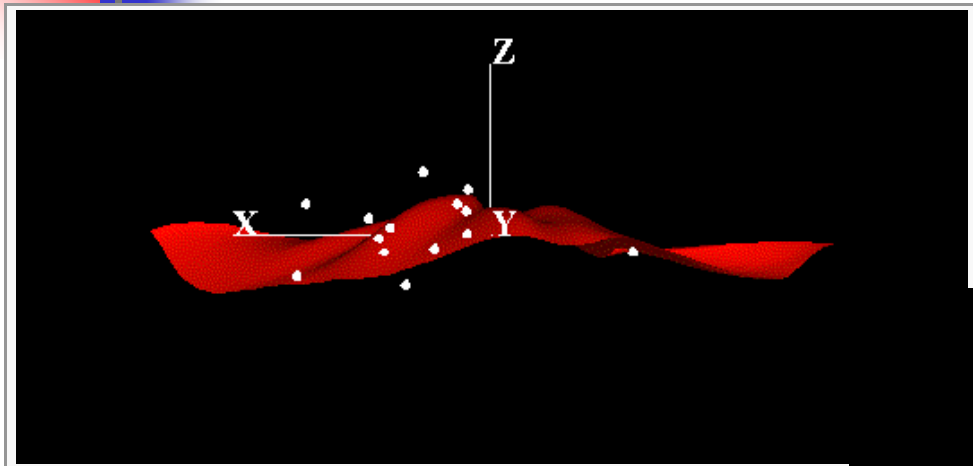


Non-Linear Local Registration (NLL):

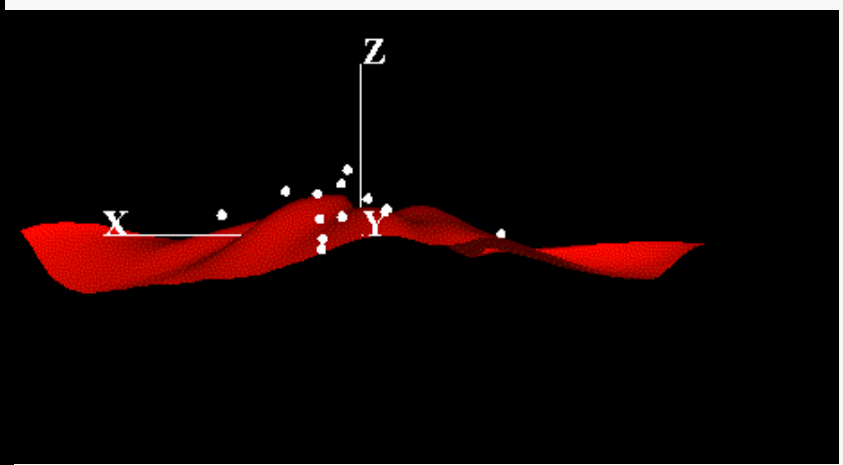
Use of thin plate splines



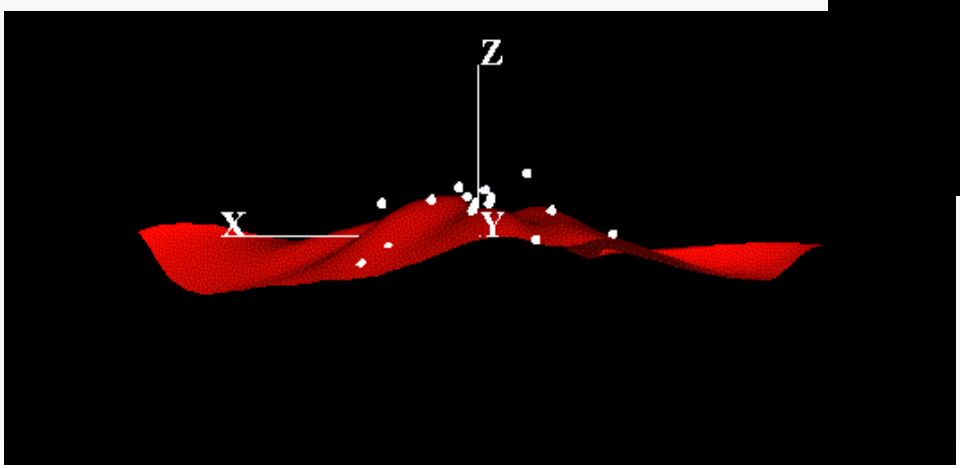
Somatotopy around the principal mode using the non-linear local method (NLL)



Little finger



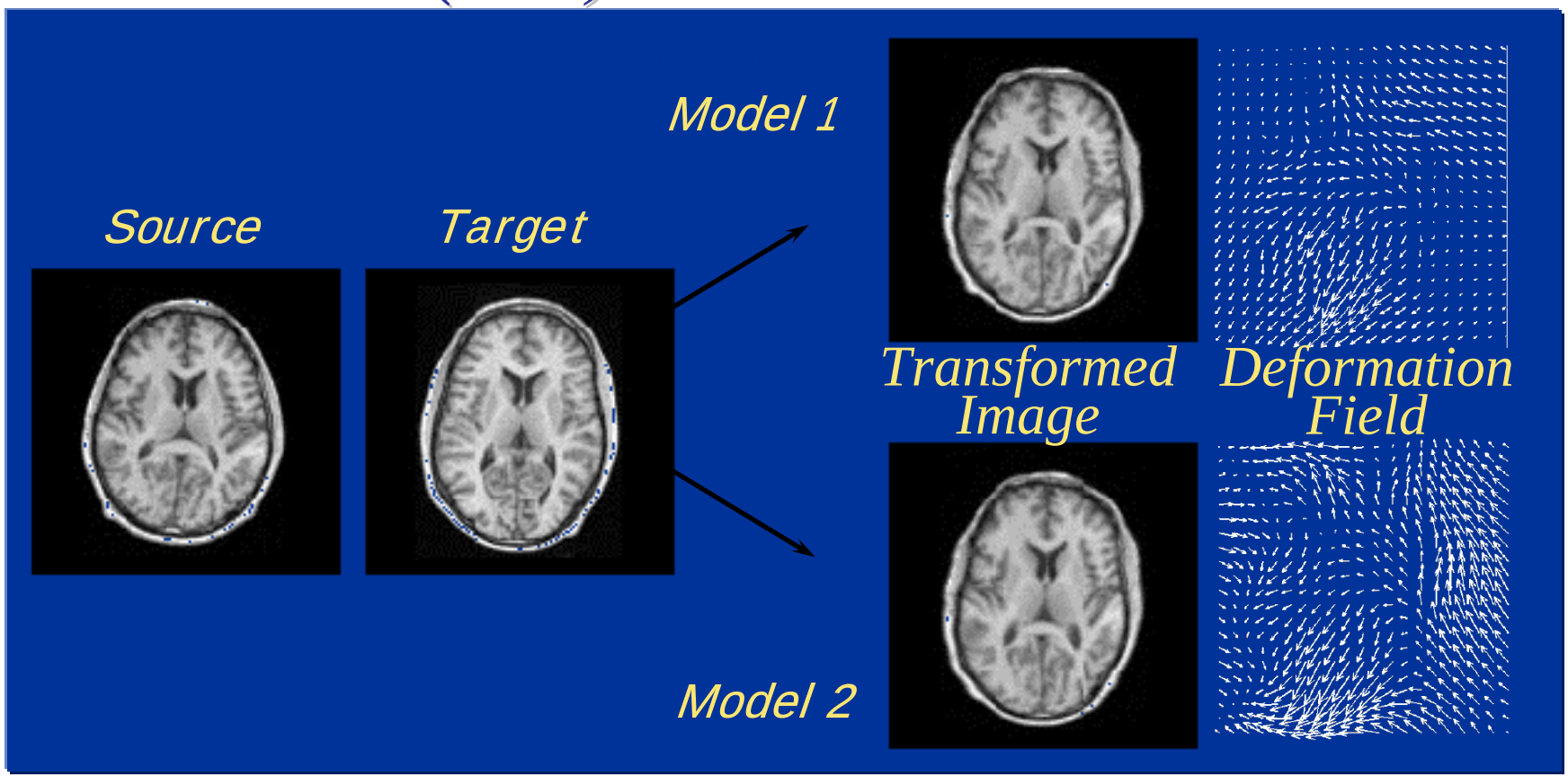
Index



Thumb

Deformable Registration: Global, iconic or photometric methods

Find a the transformation between one reference (atlas) and one individual



Adaptive Non Rigid Registration:

Using optical flow and robust estimators (RoMEO©)

- General formulation (optical flow estimation):

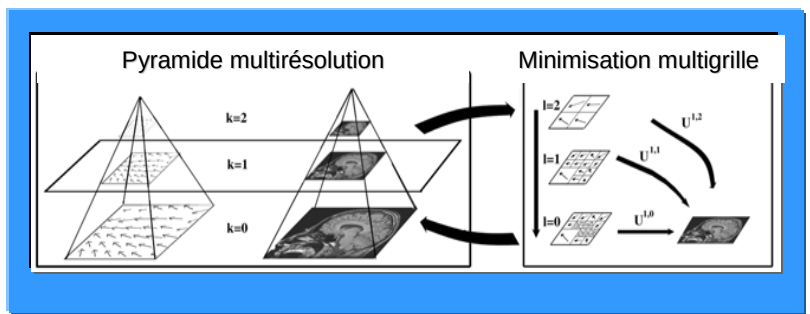
$$U(\omega; f) = \sum_{s \in S} \left[\nabla f(s,t) \cdot \omega_s + f_t(s,t)\right]^2 + \alpha \sum_{\langle s,r \rangle \in C} \left\|\omega_s - \omega_r\right\|^2$$

- Robust estimation of the deformation field :

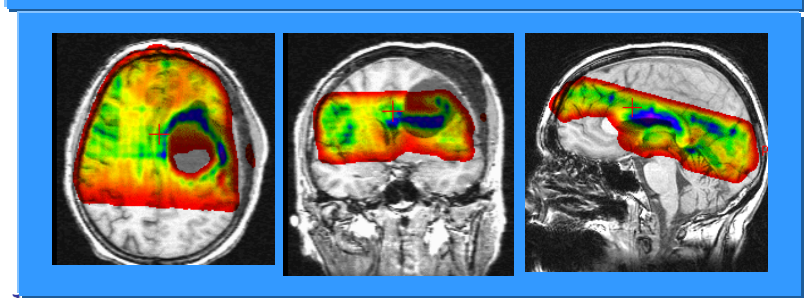
⇨ Reduce the sensitivity to noise and preserve the deformation discontinuities:

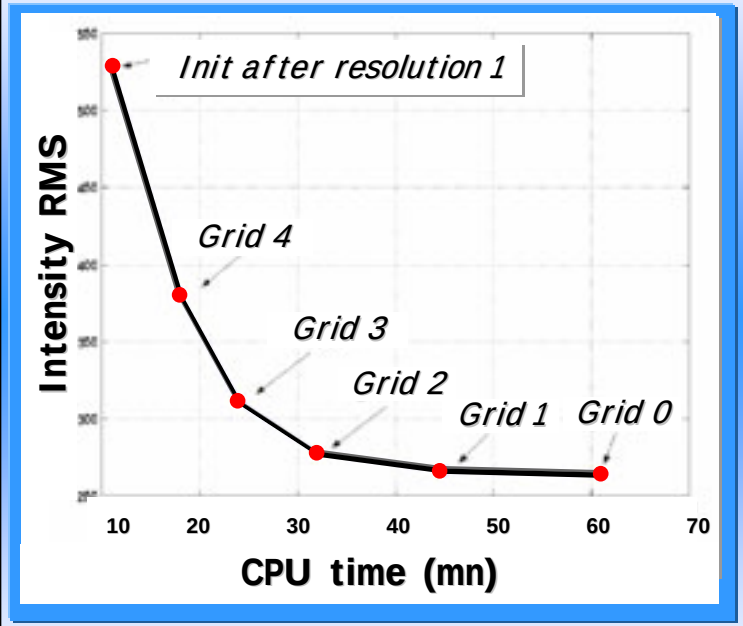
$$U(\omega, \delta, \beta; f) = \sum_{s \in S} \delta_s \left(\nabla f(s,t) \cdot \omega_s + f_t(s,t)\right)^2 + \varphi_1(\delta_s) + \alpha \sum_{\langle s,r \rangle \in C} \beta_{sr} \left\|\omega_s - \omega_r\right\|^2 + \varphi_2(\beta_{sr})$$

- Adaptative multigrid algorithm:

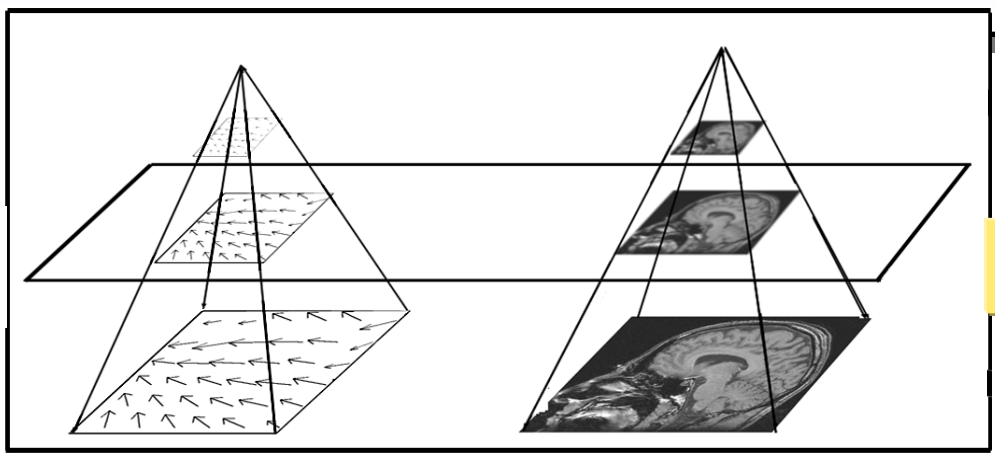


⇨ Extensible to other similarity functions (e.g. fMRI registration):

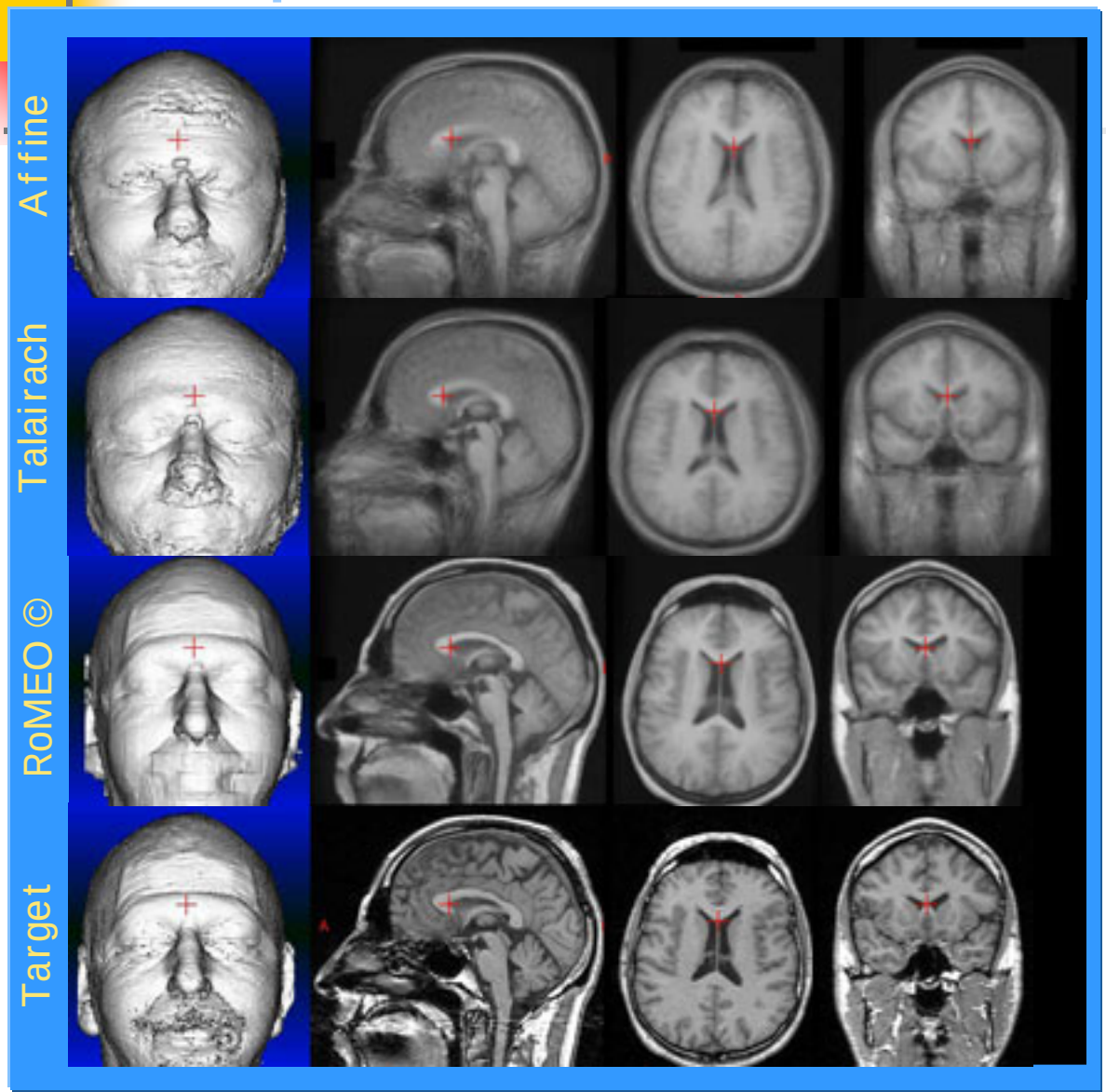


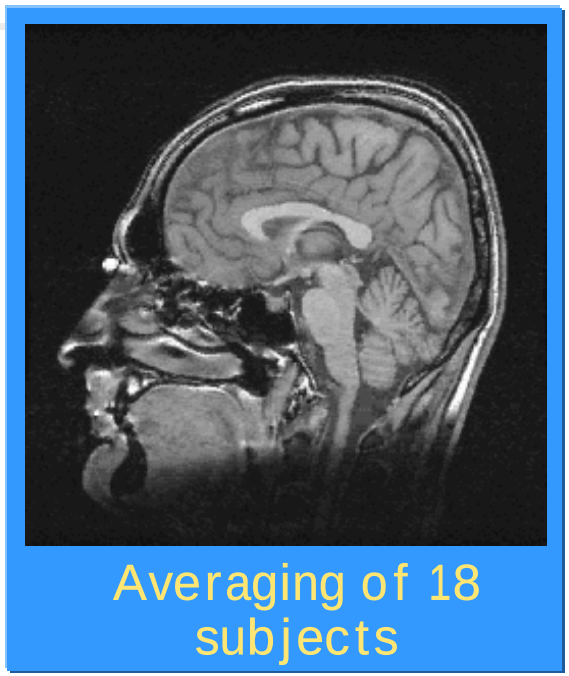


Multiresolution Pyramid

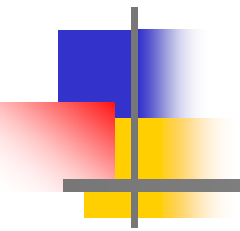


Deformable Registration : Spatial Normalization





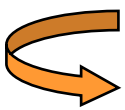
Averaging of 18 subjects



Hybrid Approach

Hybrid approach:
Cooperation between local and global approaches

- Global, or “photometric” method:
  - Image registration based on image information
  - Provides a dense deformation field
- Local, or “geometric” method:
  - Rely on landmarks (points, surfaces, ...)
  - Use an interpolation function (e.g. TPS)



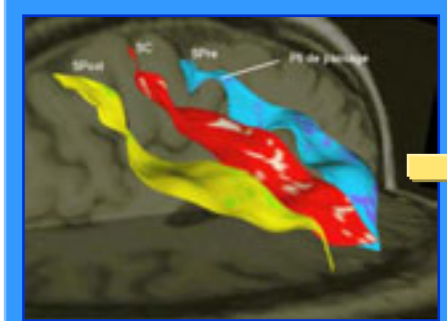
Cooperative approach, where geometric and photometric information are combined into the same framework

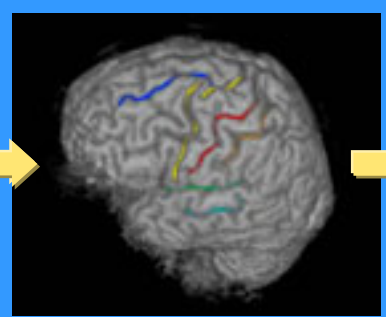
Hybrid deformable registration : Introduction of sparse constraints (JULIET©)

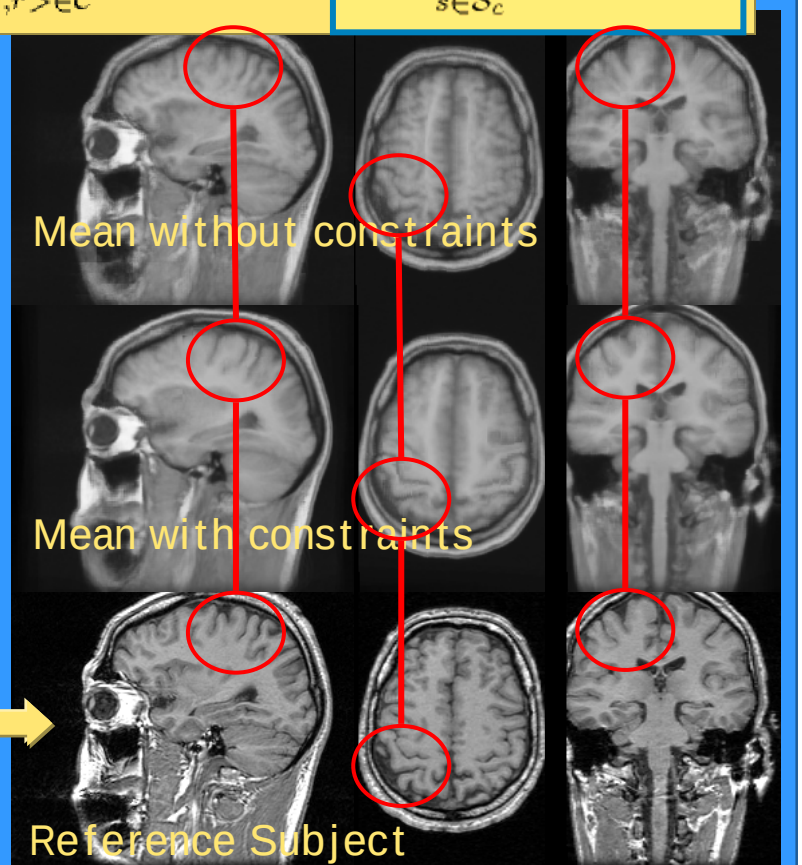
- Use of global constraints (e.g. optical flow) :

$$U(\boldsymbol{w}; f, \boldsymbol{w}^c) = \sum_{s \in S} [\nabla f(s,t) \cdot \boldsymbol{w}_s + f_t(s,t)]^2 + \alpha \sum_{<s,r> \in \mathcal{C}} ||\boldsymbol{w}_s - \boldsymbol{w}_r||^2 + \alpha^c \sum_{s \in \mathcal{S}_c} ||\boldsymbol{w}_s - \boldsymbol{w}_s^c||^2$$

- Matching of homologous structures (e.g. sulci)
- Taking into account possible interruptions between sulci

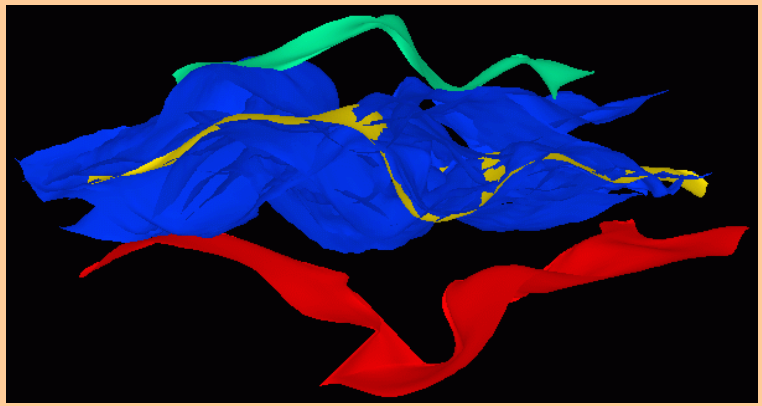




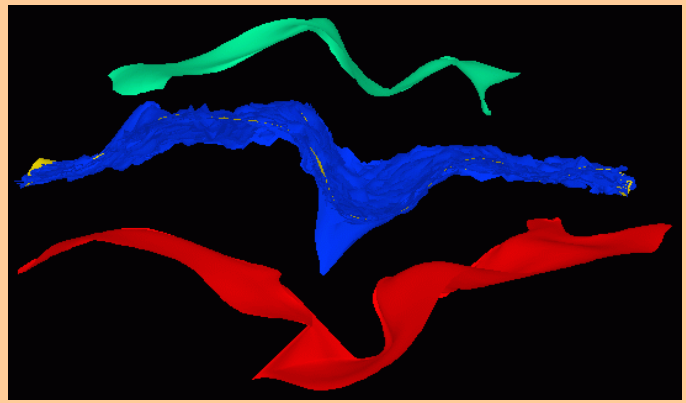


Deformed central sulci (from 18 sujects)

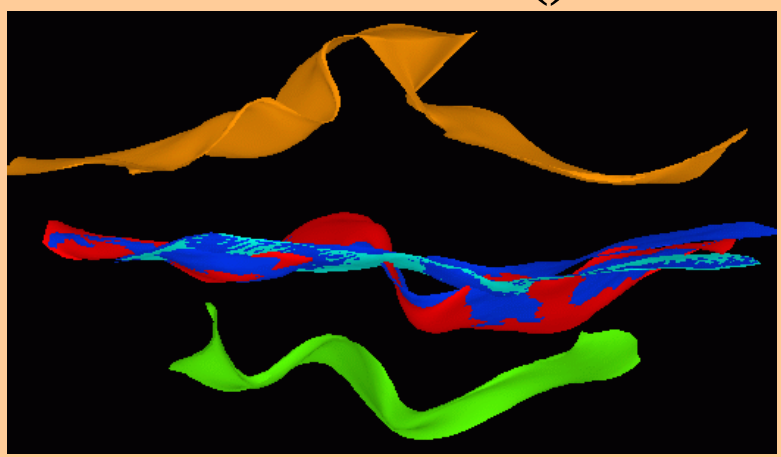
Without constraints



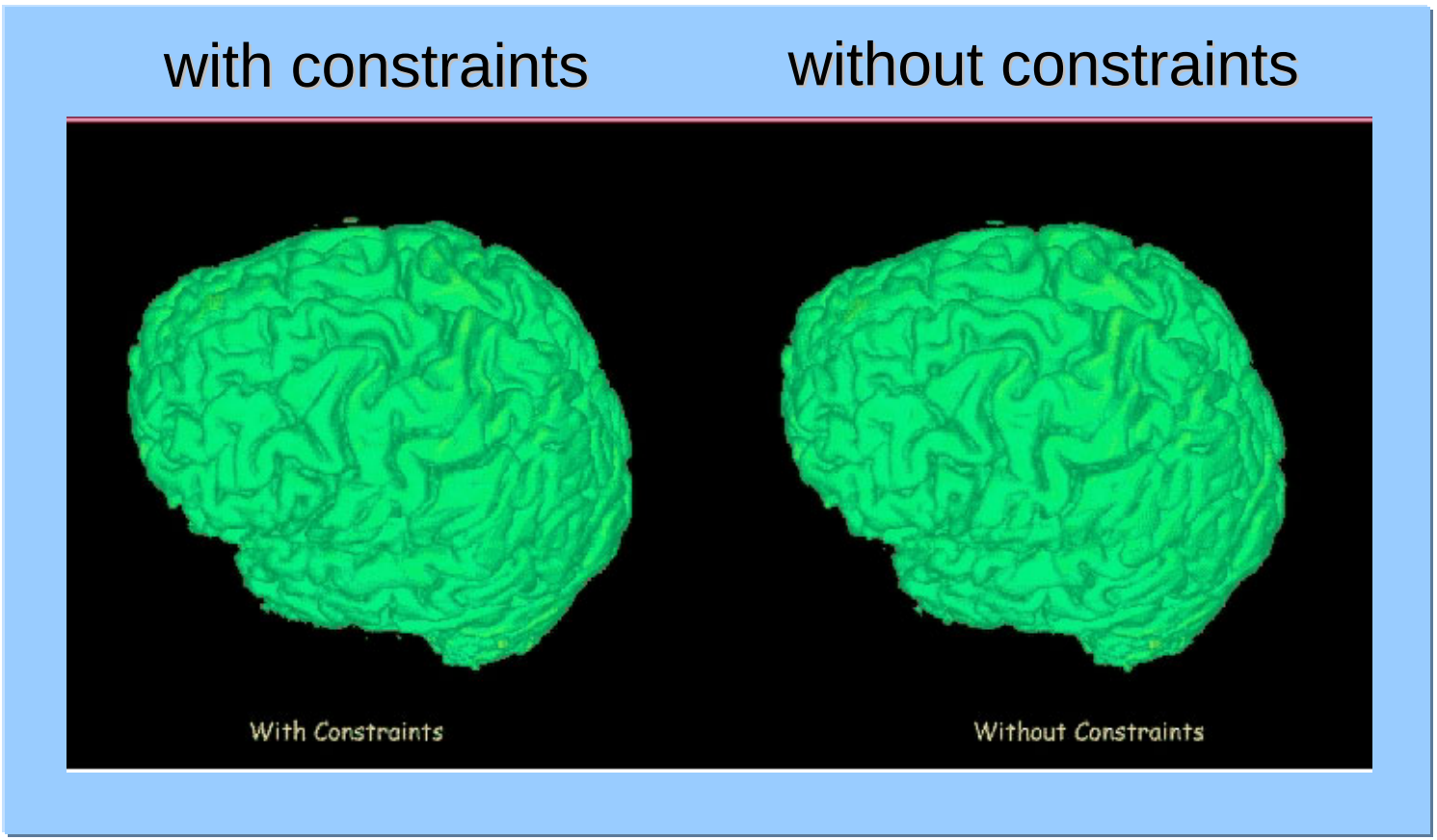
With constraints



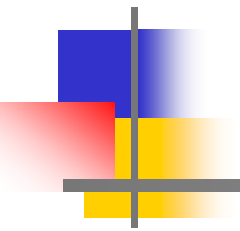
Mean sulci ()



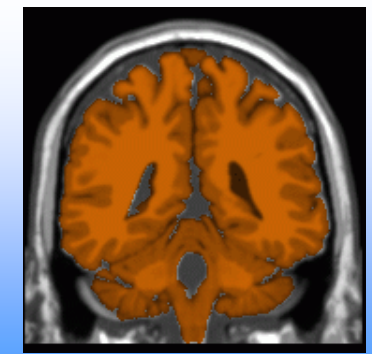
Visualization of the cortical deformation



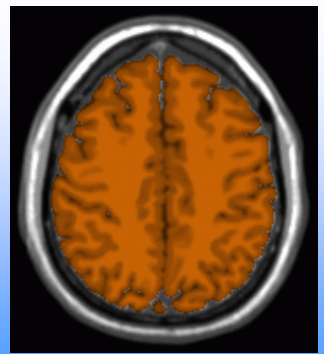
Cooperation between Segmentation and Registration Tasks

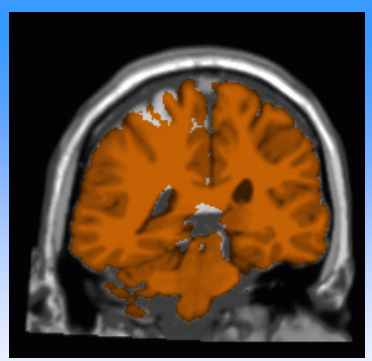


Deformable Registration and Segmentation

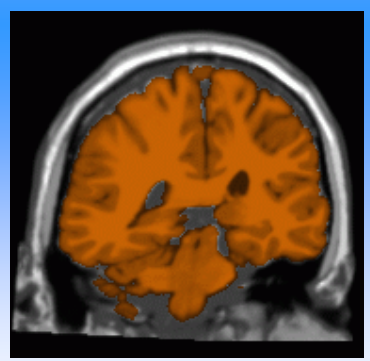


Atlas

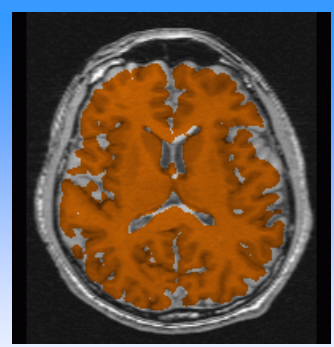




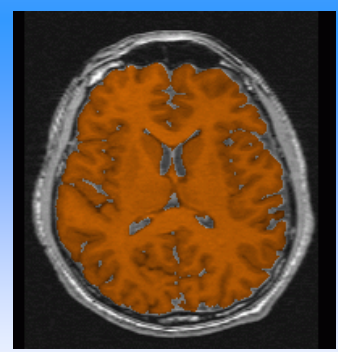
Deformable Registration



Deformable Registration + Level Sets (simulation)

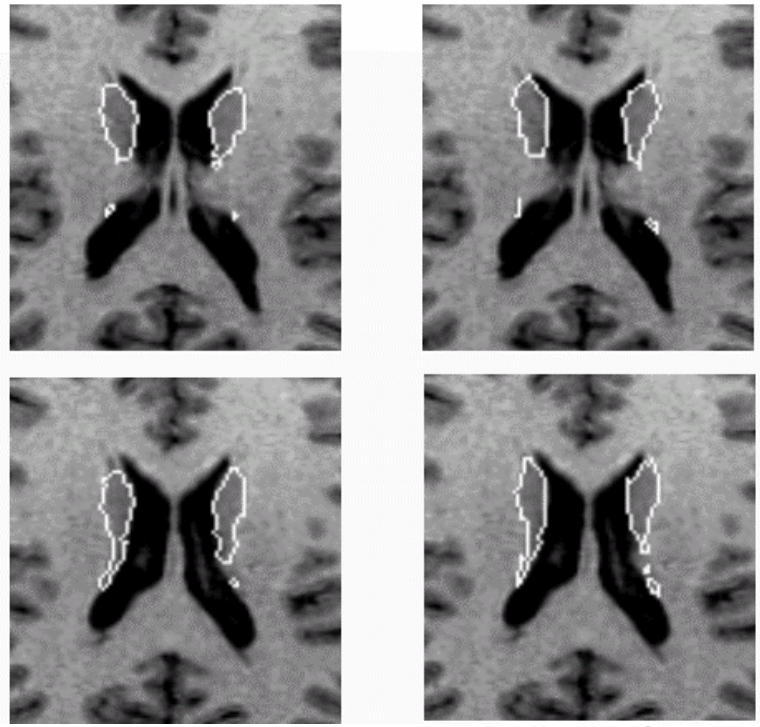


Deformable Registration



Deformable Registration + Level Sets (real data)

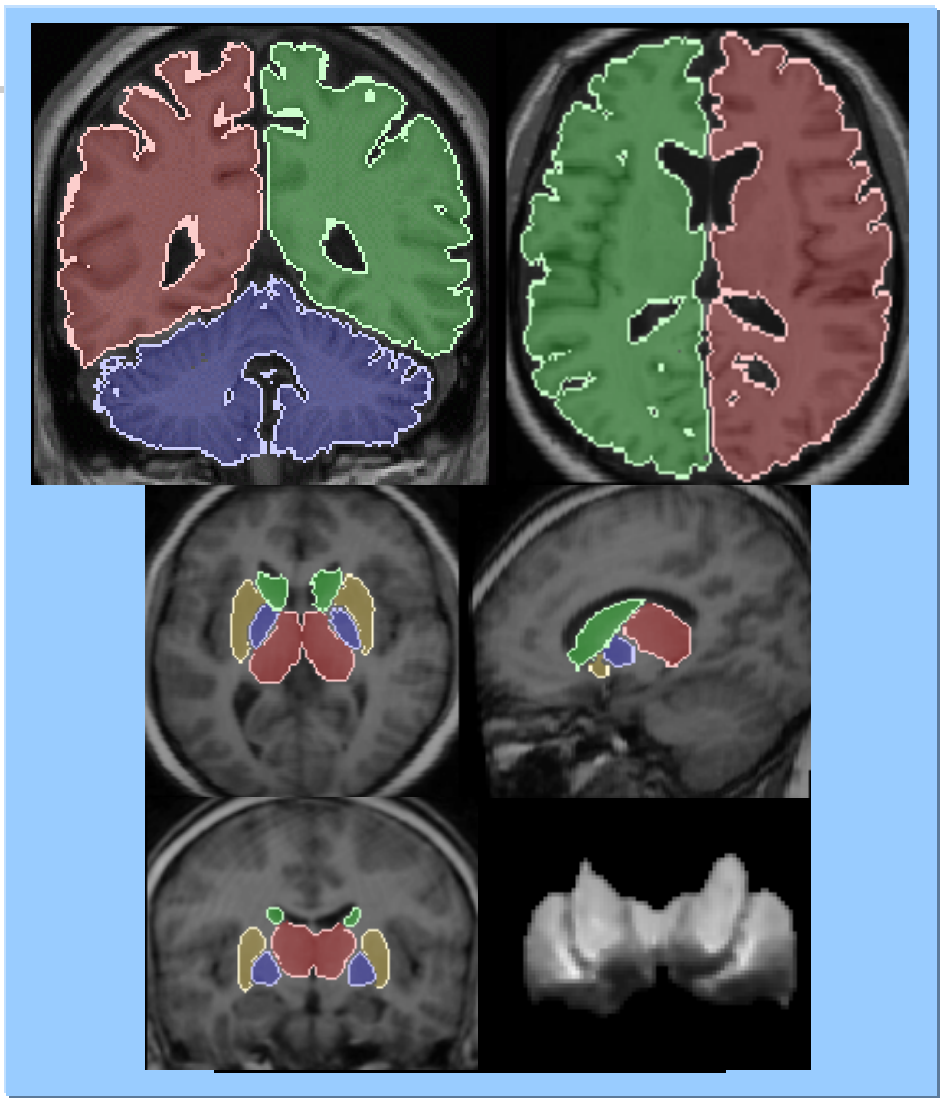
Atlas Based Segmentation *Expert Segmentation*



(Source: [Collins *et al*, IPMI'95])

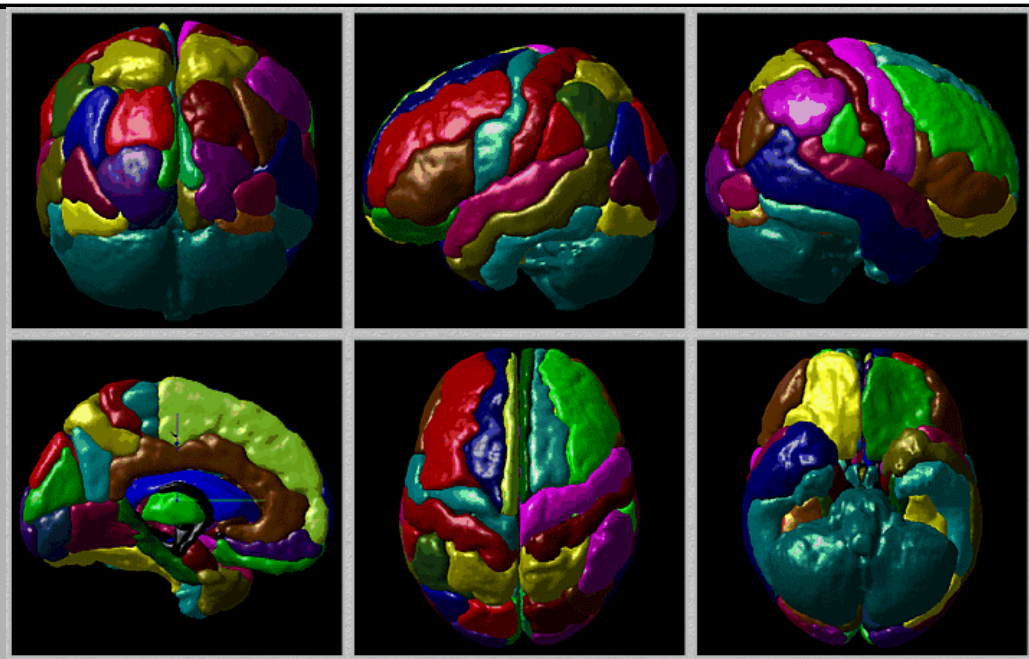
Cooperation between Deformable Registration and Segmentation

- Image preprocessing
  - noise reduction, bias field correction
- Deformable registration with a template (atlas)
  - Selection of the structure of interest from the atlas
- Segmentation of brain structures
  - Active shape (e.g. level sets) for refining the atlas-based segmentation

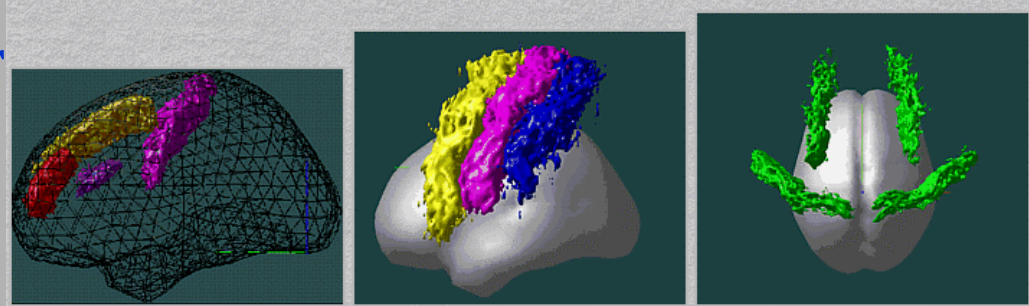


Deformable Registration: Study of the Anatomical Variability

Probabilities of cortical labels
(max proba)

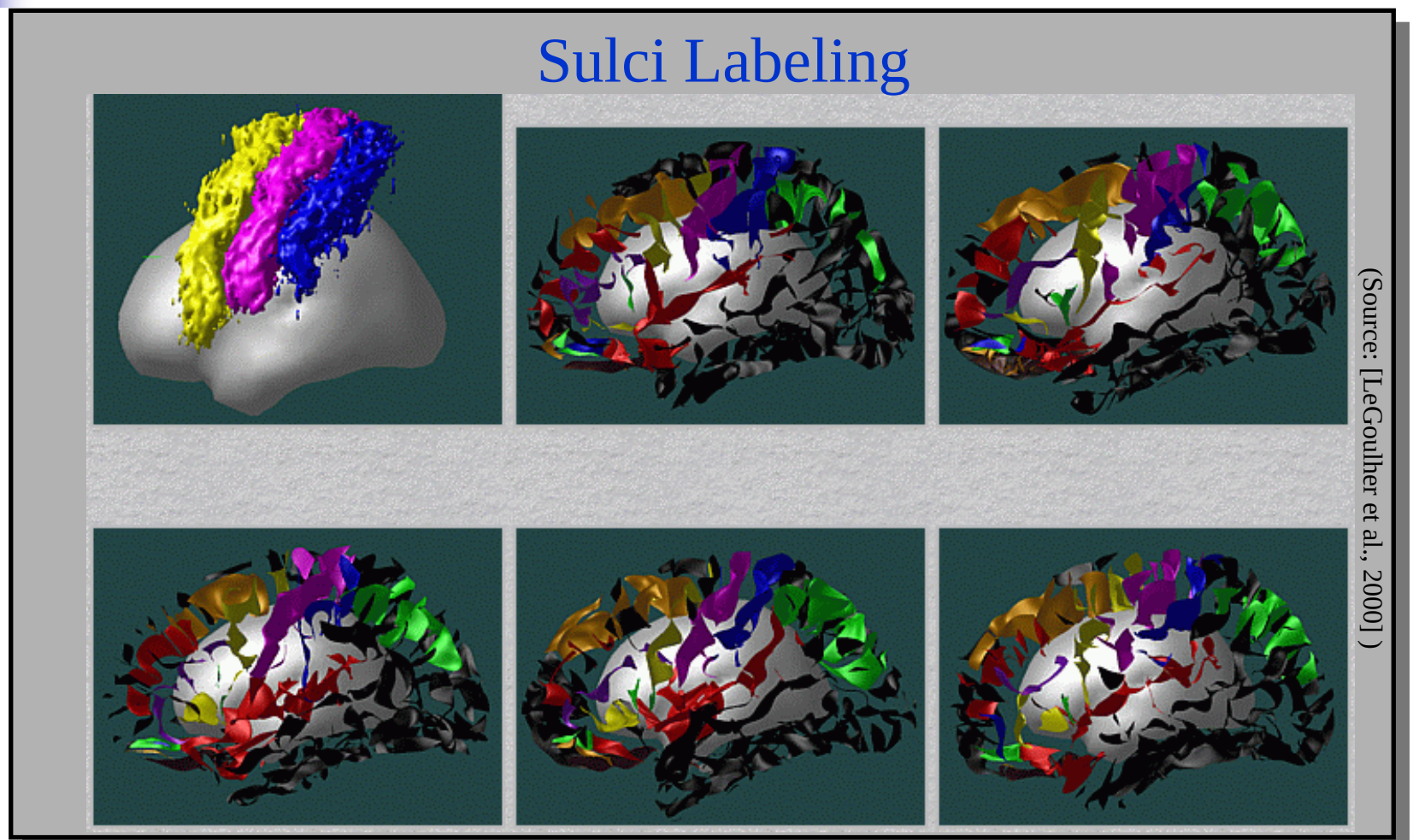


Probabilities for Sulci Occurrence
(> 10%)

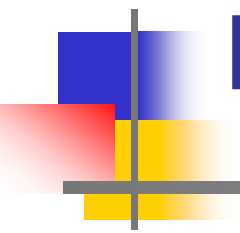


(Source: MNI, U. McGill, Montreal)

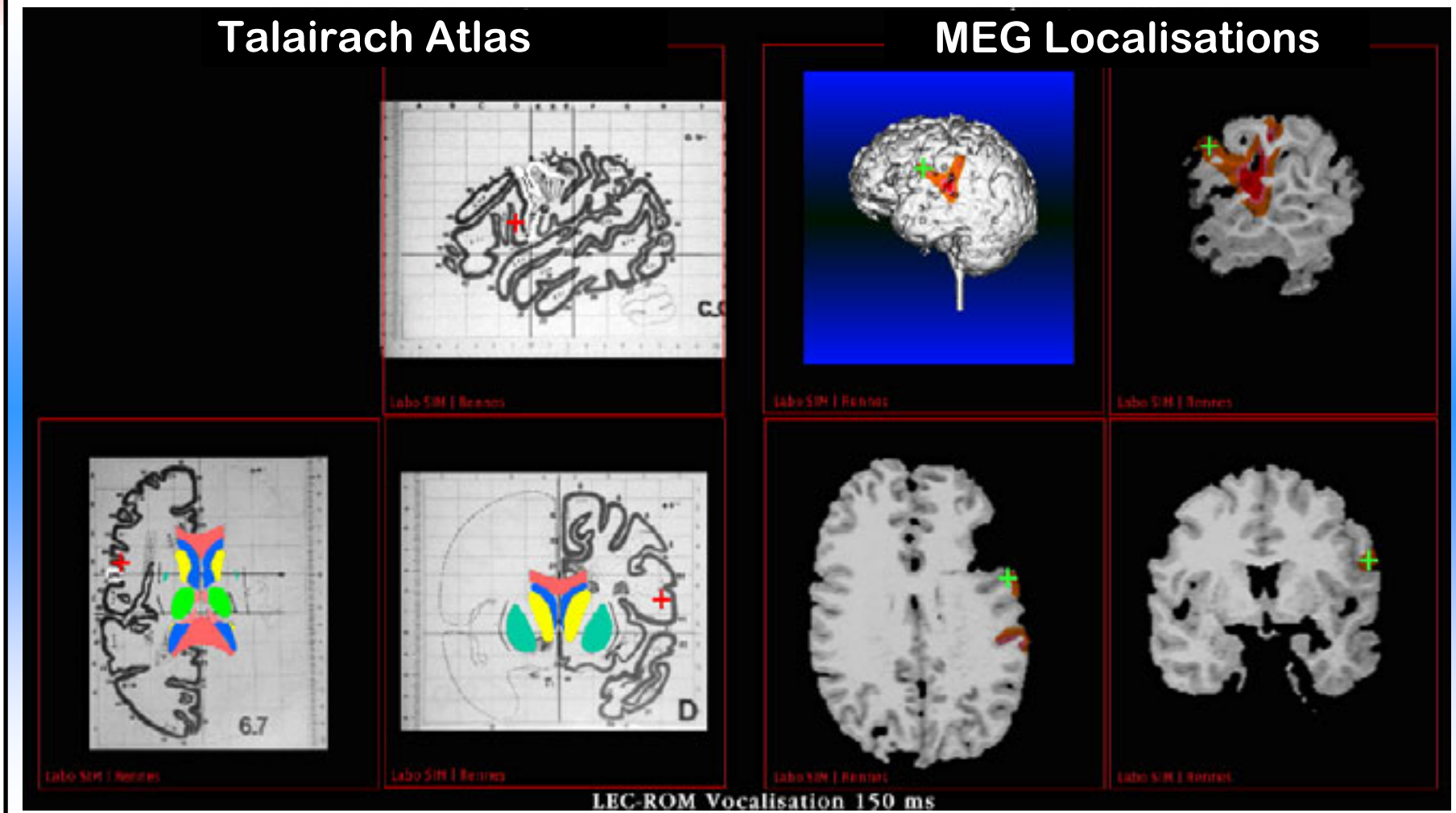
Deformable Registration: Labelling from atlas



Data Fusion of Anatomical and Functional Brain Images

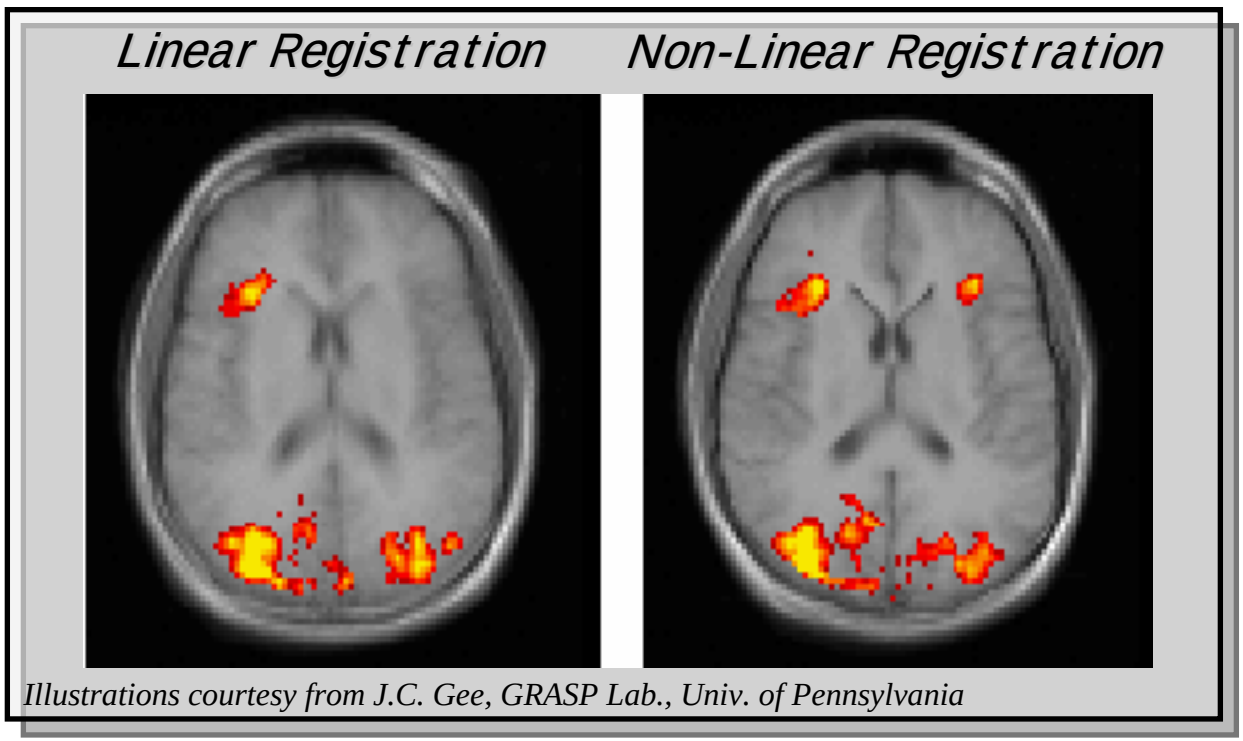


Deformable Registration for Anatomo-Functional Imaging



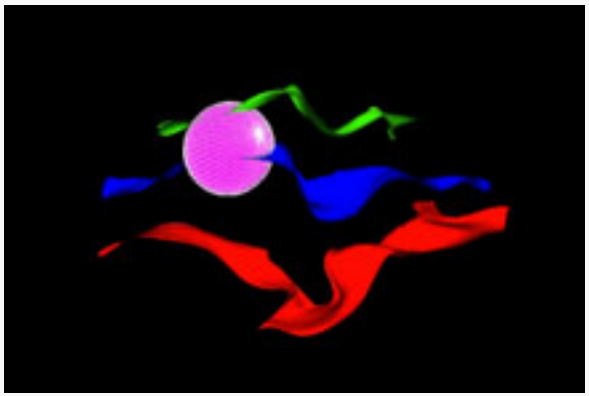
Spatial Normalization for the Analysis of Functional Data

Example of comparison of average activation responses

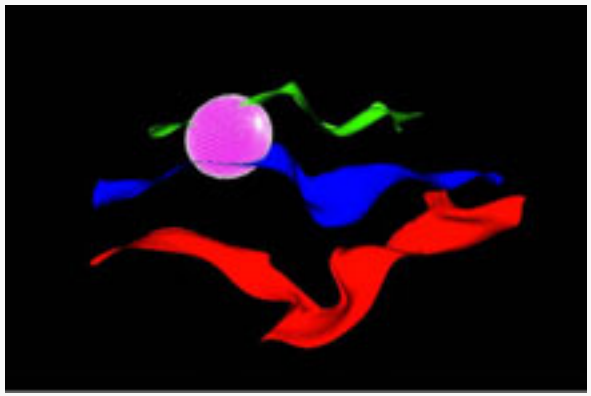


Illustrations courtesy from J.C. Gee, GRASP Lab., Univ. of Pennsylvania

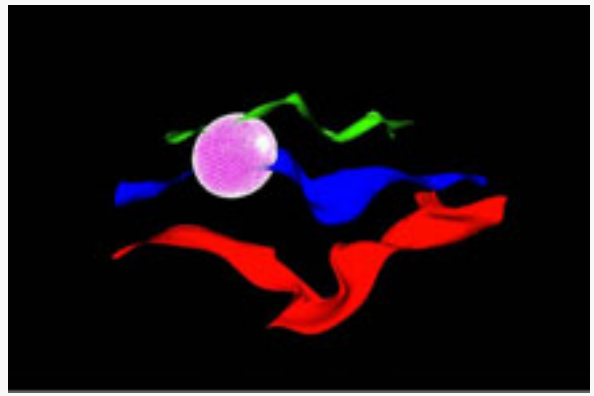
Mapping of the somatotopy using global and hybrid deformable registration methods



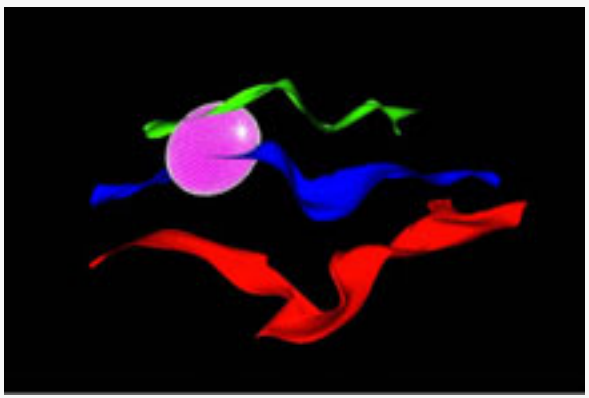
Mutual Inf. Method (M)



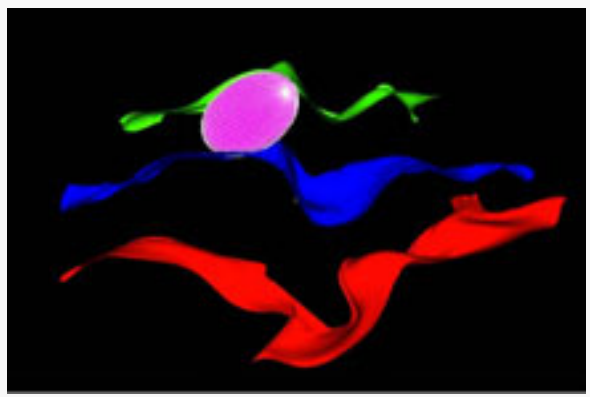
Talairach Method (P)



SPM Method (S)



Romeo Method (R)

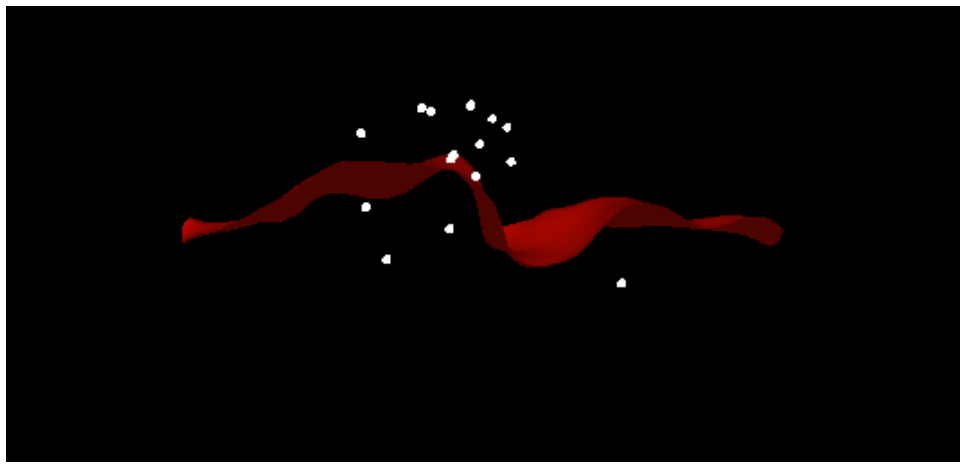


Juliet Method (H)

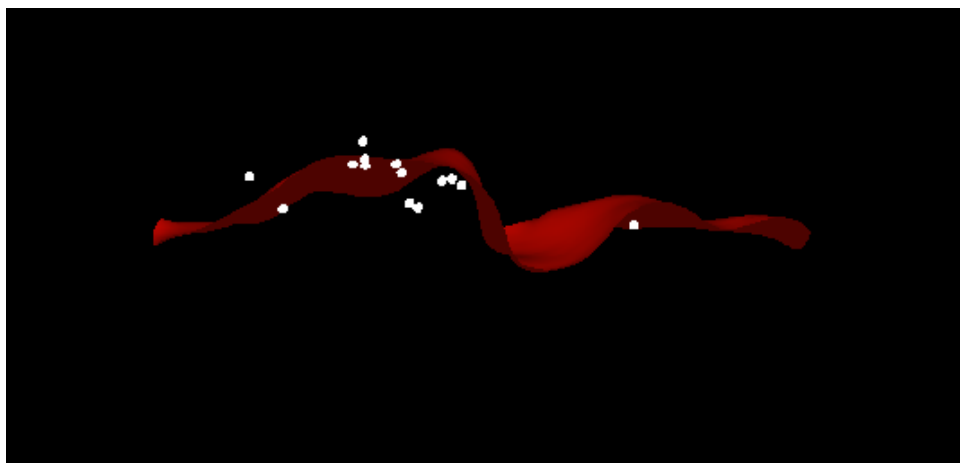
Gaussian Ellipsoid at 3σ for 15 subjects

Comparative Somatotopy : local method *vs* hybrid method

Juliet
(hybrid deformable registration method)



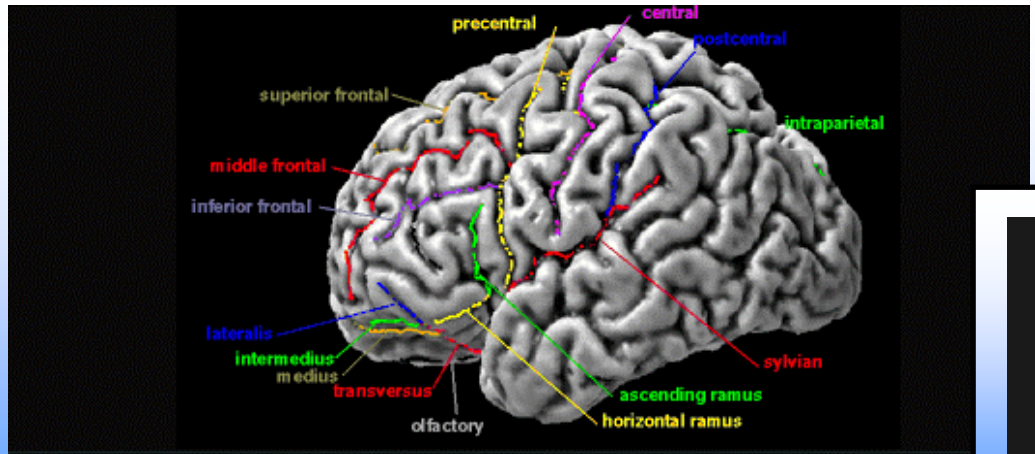
Non-Linear Local deformable registration method

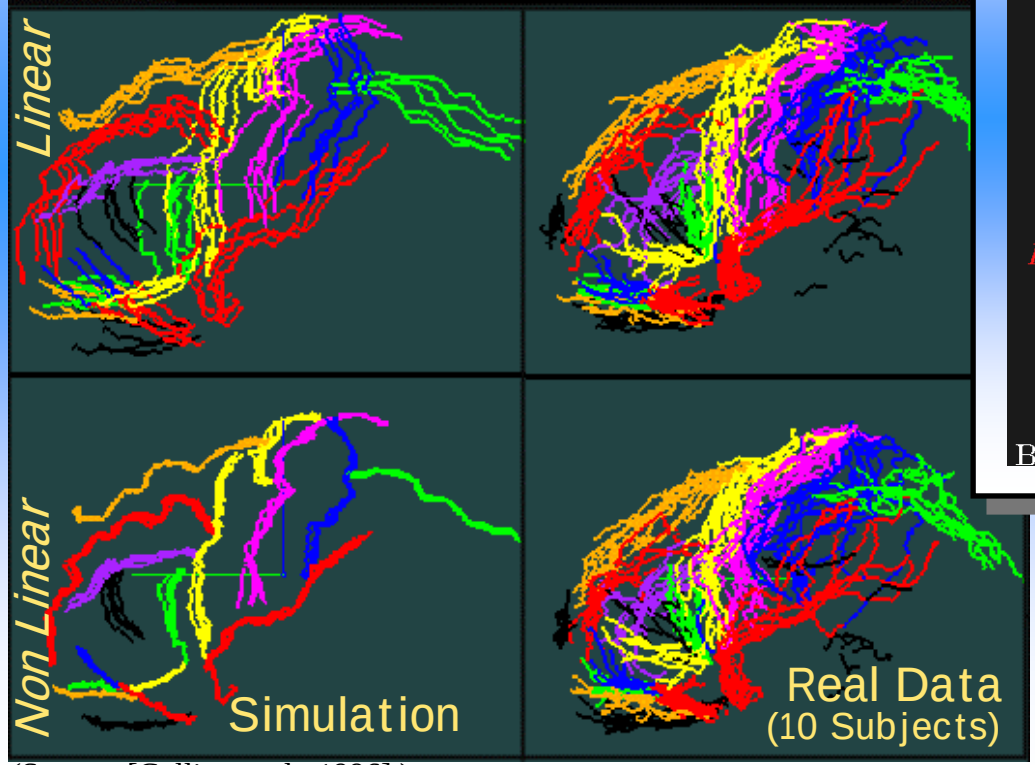


Deformable Registration : Limits

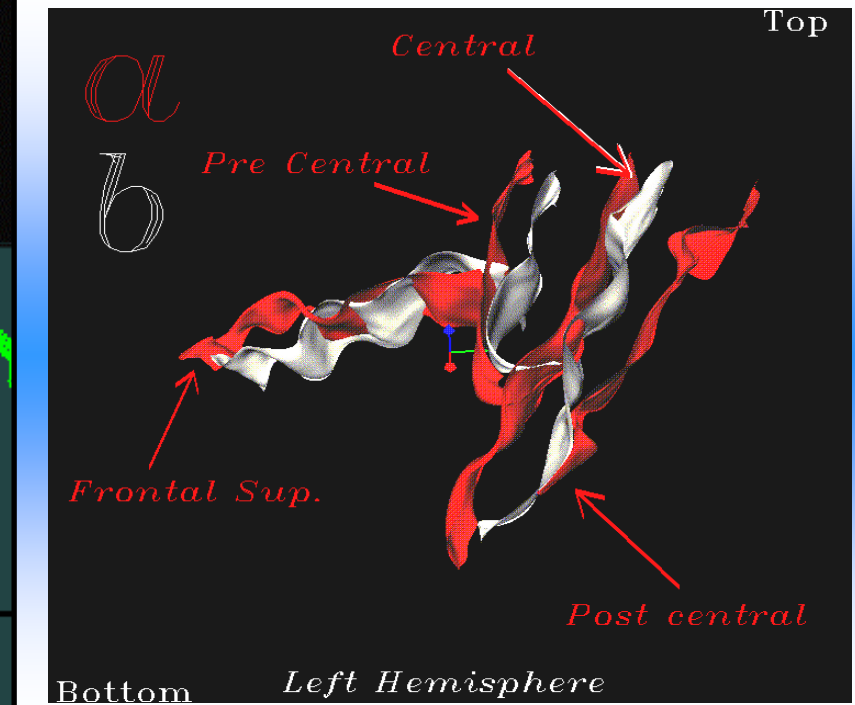
- In General
  - Validation/Generality of methods
- Segmentation/Labeling
  - Labeling of highly variable structures (e.g. marginal cortical sulci)
- Atlas matching methods using global approaches
  - Barely efficient on cortical anatomy
  - Source dependent
  - Not yet real-time

Deformable Registration: Limits



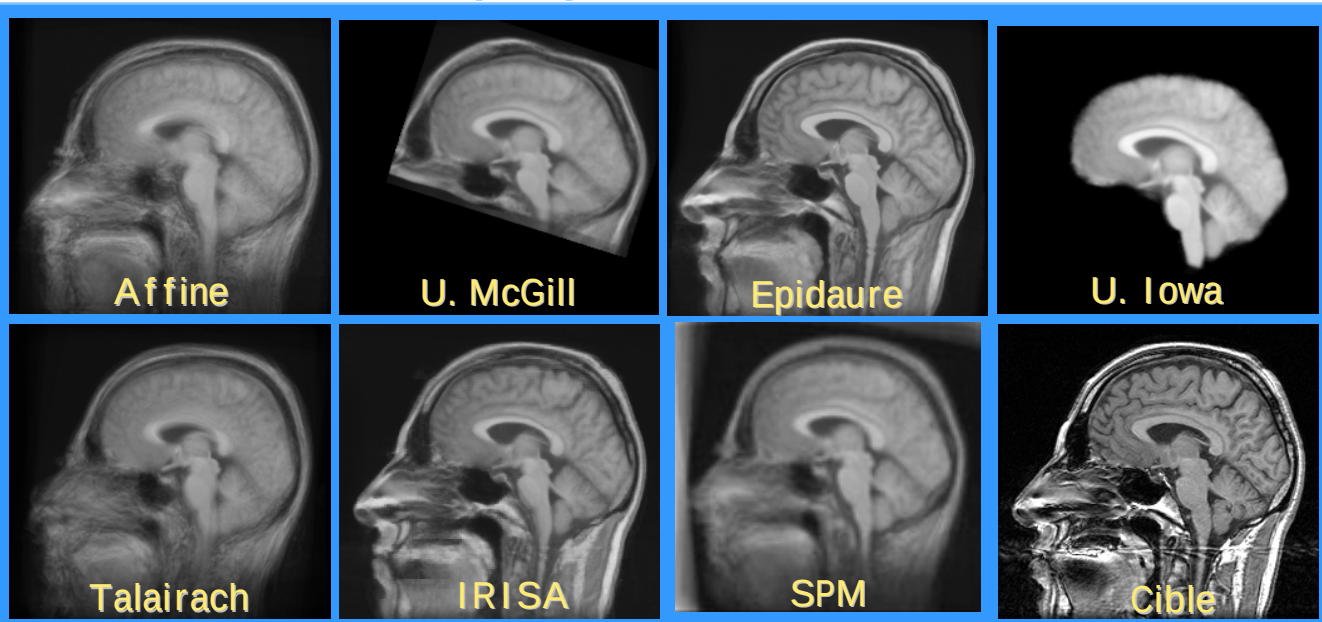


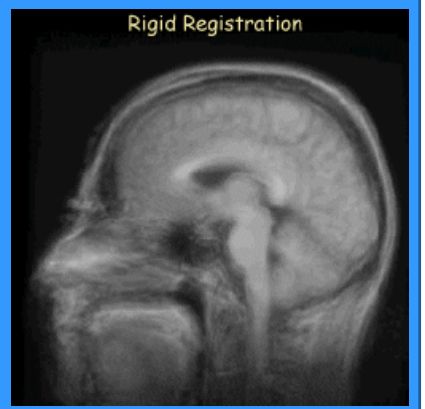
(Source: [Collins et al., 1996])



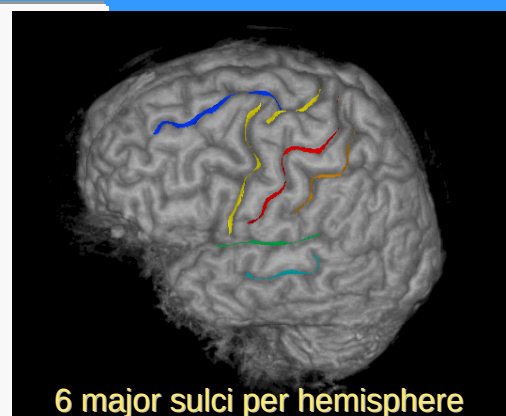
Deformable Registration:

International project for evaluation of non-rigid registration



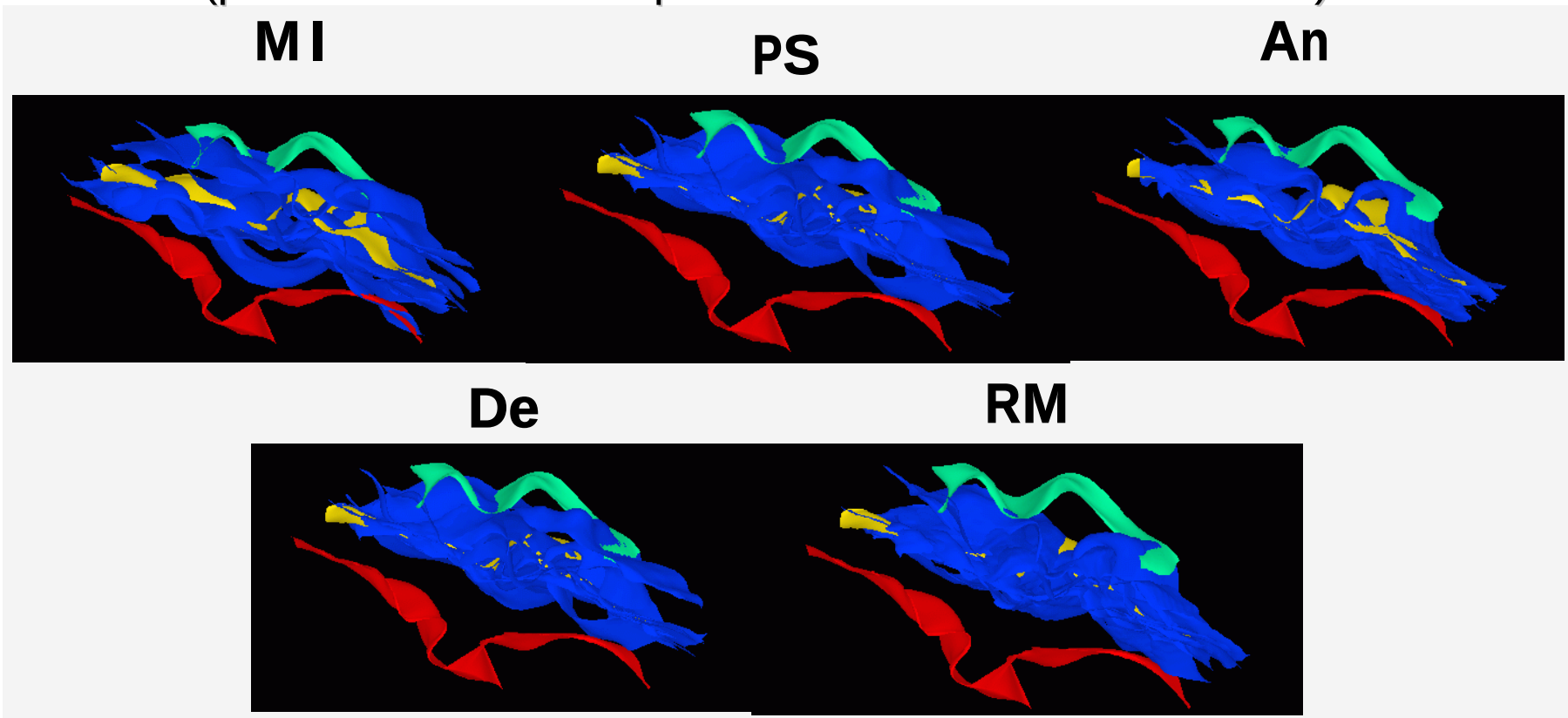


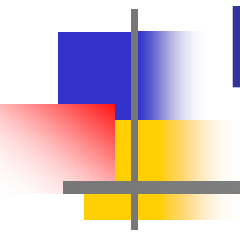
- Aim of the study
  - Anatomical and functional validity of the registration
  - On the same corpus (18 subjects)
- Others Participants:
  - U. McGill (L. Collins), Epidaure Project INRIA, U. Iowa, (G. Christensen), SPM, (J. Ashburner)
- Criteria
  - Anatomically meaningful
  - Local and global measures
  - Not related to the similarity used to perform the registration



Local Criteria on sulcal matching (highly variable)

- Use of cortical sulci (anatomical and functional landmarks)
- Visualization of overlapping deformed left central sulci (performed also on superior frontal and on lateral sulci)



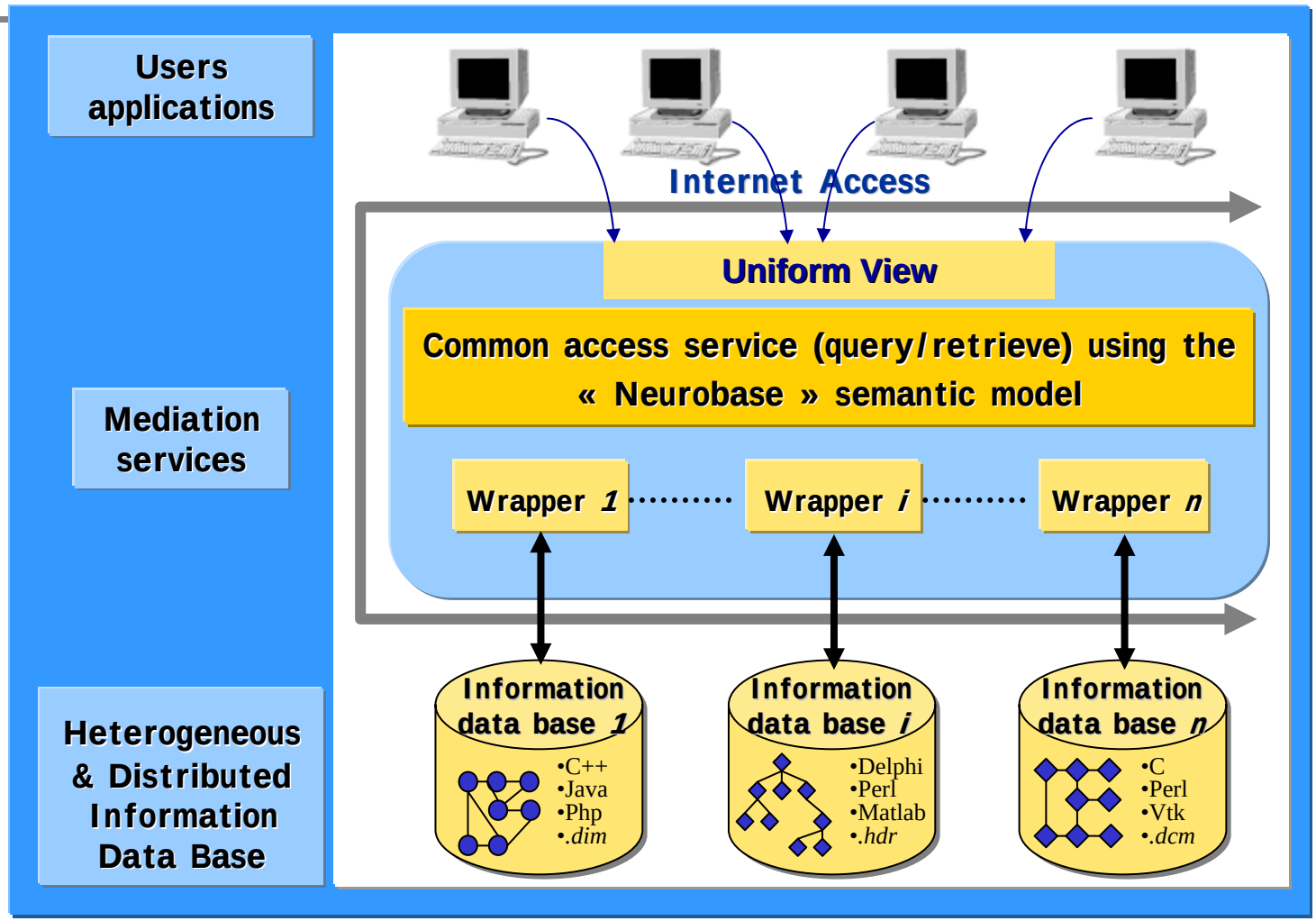


Perspectives

Data Fusion and Registration Perspectives

- Needs to take into account local and global constraints in the deformable registration process (hybrid registration)
- More concerns about the clinical practice
  - pre-surgical mapping
  - intra-operative and real time imaging
  - Cope with missing tissues (registration of dissipative material)
- Introduction of statistical information for the guidance of the deformation
- Tighter links between registration and segmentation (e.g. thru active surface formulation)

Sharing heterogeneous and distributed resources (data, processing)



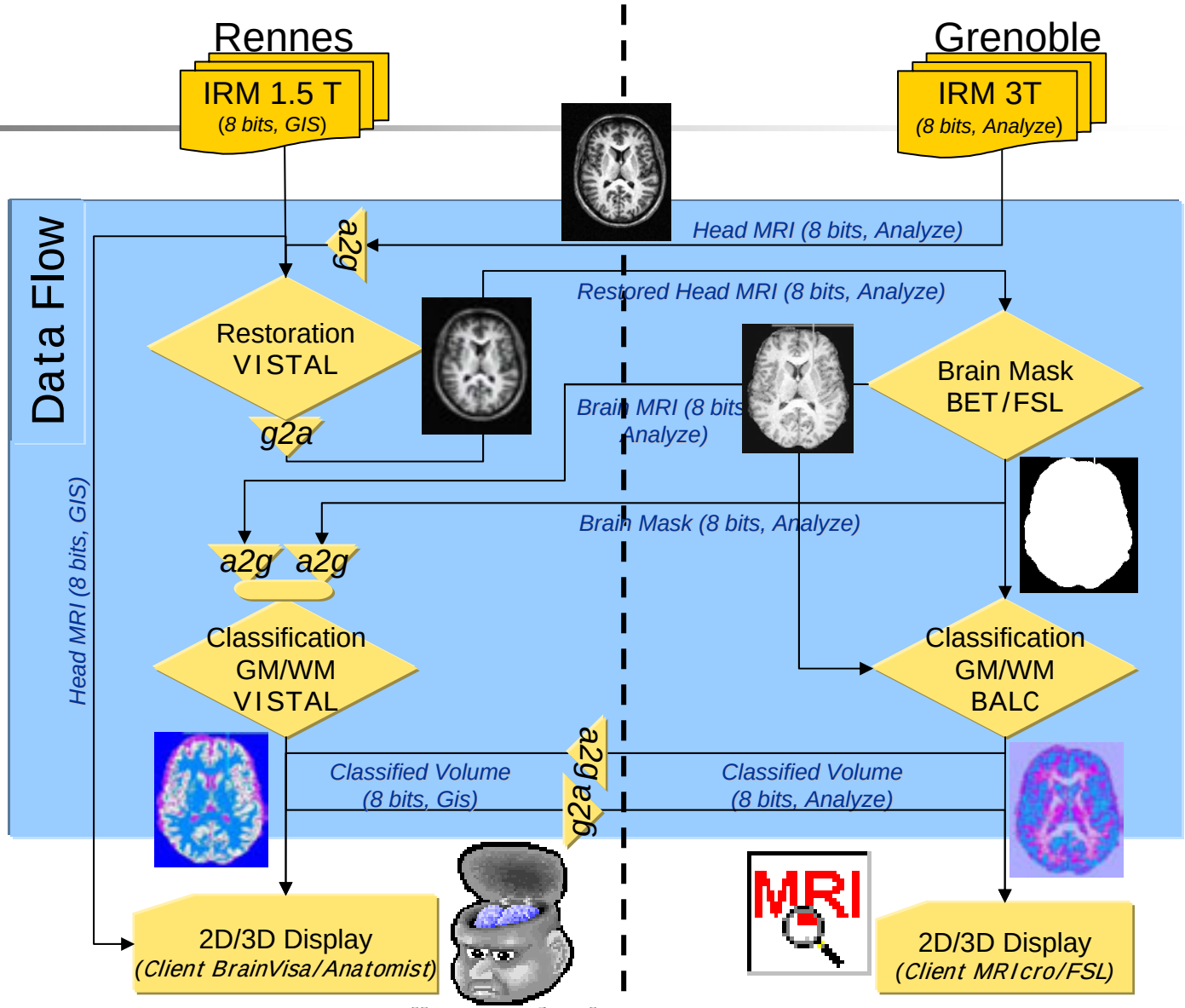
Sharing of medical imaging resources: Issues

- Objectives:
  - Follow the growth of the communication and exchange infrastructures (e.g. Internet)
  - Follow the emergence of "virtual" networks of users (e.g. clinical groups of research)

- Applications of information and grids technologies in health:
  - Creation of "virtual" cohorts
  - Research on the singular diseases (search for « unlikely facts »)
  - Validation / certification of new drugs

- Research Issues
  - Combine Grid Computing and Semantics Grids technologies in the field of medical imaging
  - Evolutive and adaptive workflows in Medical Imaging (user interactions, heterogeneity, ...)
  - Integrate the semantic web technologies into clinical research

Heterogeneous and Distributed Workflow/DataFlow



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