Medical Imaging: Data Fusion in 3D Medical Imaging

Christian Barillot
CNRS Director of Research

VisAGeS U746 as a component of the “IRISA” Institute
(http://www.irisa.fr)

- IRISA is a publicly funded research institute:
  - Co-funded by INRIA, CNRS and Univ. of Rennes 1.
  - a staff of 650 people, including 200 research faculty staff, 100 technical and administrative staff and 150 postgraduate students
  - Net revenues: 10 M€/year (including 6.5 M€ from grants)
  - Per year around 500 publications, 40 PhD, 10 conferences
- Research Center on Information Technologies and Applied Mathematics:
  - Goal: bring together mathematicians, automated systems analysts, computer scientists and signal and image processing people
  - 30 research teams centered around 5 major scientific topics:
    - networks and systems
    - software engineering and symbolic computation
    - man-machine interaction, images, data and knowledge
    - simulation and optimization of complex systems
    - Modeling of living organisms
- And their application in many fields:
  - telecommunications, multimedia, transport, medical science, genomic, emerging technologies applied to health, environment etc.
IRISA in Rennes, Brittany (Roazhon) (http://www.ville-rennes.fr)

- Provincial Capital
- City area of around ~450 000 people
- One of the most fast growing city area in France
- 2 Universities and > 20 post-graduate schools (~60 000 students)
- World’s smallest city to have a subway
- Founded around 57 BC (Condate)
- More than 80 large research centers (public and privates)
  - INSERM, CNRS, INRA, INRIA, Canon, France Telecom, Thomson, Lucent, Mitsubishi, Wandel & Goltermann

VisAGeS U746 at Short (http://www.irisa.fr/visages)

- 4 affiliations
  - INSERM (National Institute of Health and Medical Research)
  - INRIA (National Research Institute of Informatics and Automation)
  - CNRS (National Center for Scientific Research)
  - University of Rennes I
- The only team to be jointly affiliated to INSERM and INRIA
- ~25 people, including 7 research faculty staff (incl. 2 MD’s), 3 technical and administrative staff, 9 PhD, 2 Post-docs, 7 associate faculty
- Offices in 2 locations:
  - Univ. Hospital and IRISA/INRIA (10mn by car)
  - Transparent “virtual” office (network, admin, agenda)
- People have office at both locations
Plan of the presentation

- 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
Coming issues

- Conception of the surgical room of the future
  - Integration of intra-operative multimodal sensors and effectors (e.g., robots) at different scales (from the molecule to the organ through the cell)
  - Guidance of surgical information sources by observations and knowledge
- Better understand the behavior of normal and pathological systems, at different scales
  - Imaging the pathologies, from the organ level to the cell and the molecule
  - Modeling normal and pathological group of individuals (cohorts) from image descriptors
- Creation of virtual organizations of medical imaging actors thru the dissemination of GRID and semantic web technologies in e-health, for:
  - The creation of "virtual" cohorts
  - The research of new specific biomarkers from imaging
  - Data mining and knowledge discovery from image descriptors
  - 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

Magnetic Resonance Imaging (MRI)

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

Extended temporal hypo metabolism

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

MRI + interictal SPECT (HMPAO)  Brain MRI + ictal SPECT

Intra cerebral electrodes implant in stereotactic conditions

MRI

Registration of 3D referential

Angiography

3D - 2D Projections

stereotactic referential
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)
MEG: Spatio-temporal analysis of interictal spikes


C. Barillot, « Medical Imaging II »
Epilepsy Surgery: Preoperative Planning

Functional Mapping of language areas

Silent vs Active Word Activation
Preoperative Planning: functional MRI (fMRI)

- Acquisition
- Paradigm
  - mean of activation $A$
  - Mean of rest state $R$

Detection

$A - R$

Image: "Medical Imaging II"
Epilepsy Surgery: Superposition of graphical data

Surgical resection

Electrodes landmarks

Resection
Evolution in Image Guided Neurosurgery

Image-Guided Neurosurgery: Interventional procedure (Neuronavigation)
Evolution of Preoperative Planning: More Anatomical and Functional Mapping

Adding observations during surgery: Video reconstruction
Registration of intraoperative 3D Ultrasound with pre-op MRI

**Objective:** Construct probability maps of hyperechogenic structures from MRI and Ultrasound images for registration.

**Principal:** Find a function \( f \) relating the MRI intensity of a voxel \( X(u(X)) \) with its probability to be included in the set of hyperechogenic structures:

\[
p(X \in \Phi) = f(u(X))
\]

\[
T = \arg \max_T \int p(X \in \Phi_T, T(X) \in \Phi_{MR}) dX
\]

*P. Coupe et al., IEEE-ISBI 2007*

---

Image-guided neurosurgical procedures: Current and New Issues

Integration of new models and observations

- Take into account intraoperative brain deformation (gravity, drugs, CSF leaks de LCS, exérèse ...)
- Take into account additional preoperative data (DTI, molecular)
- New information sensors during surgery (video, 3D ultrasound, iMRI, in-vivo microscopic biological imaging, molecular data)
- "Real time" fusion of multimodal intraoperative images to assist the decision process
Cooperative Scheme for Data Fusion

Intra-Individual Data 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

C. Barillot, « Medical Imaging II ».
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 $\Phi$

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

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

C. Barillot, « Medical Imaging II »
### Basic Referential

![Diagram of Basic Referential](image)

- **Image Referential**: $p(i,j,k)$
- **Instrumental Referential**: $p(u,v,w)$
- **Subject Referential**: $p(x,y,z)$

### Class of registration domains

**ONE patient**
- Intra-modality registration:
  - Post-operative control
  - Pathology tracking, Treatment probing

**SEVERAL patients**
- Intra-modality registration
- Model-based segmentation
- Registration/matching with an anatomical atlas
- Spatial normalization, study of anatomical variability

**ONE modality**
- Inter-modalities registration
- Complementarities between sources of images
- Computer assisted therapeutic planning
- Computer assisted surgery
- Anatomy-function correlation

**SEVERAL modalities**
- 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, $\Omega_s$ and $\Omega_t$ 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 $\omega$ in $\Omega_s$ to its correspondent $\Phi(\omega)$ in $\Omega_t$.

- By generalization, this transformation can be applied to the underlying images $I_s$ and $I_t$: $(I_s(x, y, z) = \Phi(I_t(x, y, z)))$
- For a given optimization method $\Psi$, the transformation $\Phi_{\theta} \in \Theta$ is computed by the optimization of:

$$\arg\min_{\theta \in \Theta} \Delta(\Phi_{\theta}(\Omega_s) - \Omega_t)$$

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

Registration: The 4 basic stages

- Definition of homologous structures ($\Omega$)
- Definition of the type of transformation ($\Phi$)
- Definition of the cost function ($\Delta$)
- Definition of the cost function optimization algorithm ($\Psi$)
Types of Homologous Structures ($\Omega$)

- Size of the manifold ($D_\mu$)
  - 0D: point ($\Omega = \text{Constant}$)
  - 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 ($D_\nu$)
  - 2D: surface, projection ($\Omega \in \mathbb{R}^2$)
  - 3D: discrete or continuous space ($\Omega \in \mathbb{R}^3$)
  - $nD, nD + t$: hypersurface, spatio-temporal ($2D + t$); ($\Omega \in \mathbb{R}^n$)

Nature of Homologous Structures ($\Omega$)

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

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

Similarity Function (Δ)

- **Definition**: The similarity function defines the objective criteria (cost) used to estimate the quality of the registration between two homologous structures ($\Omega$).

- 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, ...)

C. Barillot, « Medical Imaging II »
**Image registration:**
Measure from joint histogram

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

Registered Images
\[ \frac{1}{2} \cdot [X + \Phi(X)] \]

\[ \Phi = I \]
\[ \Phi = T_x \]

**Image registration:**
Relation between the transformation and the joint histogram
Joint Histogram:
Linear or Affine Dependencies

Optimum SSD/SAD
\[ y = x \]
\[ \text{SSD}(X,Y) = \sum_{x \in X, y \in Y} (x-y)^2 \]
\[ \text{SAD}(X,Y) = \sum_{x \in X, y \in Y} |x-y| \]

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

Optimum \( \text{Corr}(x,y) \)
\[ x = \alpha x + \beta \]
\[ \text{Corr}(X,Y) = \frac{E[XY]}{\sqrt{E[X^2]E[Y^2]}} \]

Joint Histogram:
Examples of Linear or Affine Dependencies

Joint Histogram \( (HIST(x,y)) \)
Registered Images \( \left( \frac{1}{2} [X + \Phi(X)] \right) \)

\( \Phi = I \)
\( \Phi = I'_s \)
Joint Histogram: Functional Dependencies \((e.g. \text{Correlation Ratio})\)

\[
\begin{align*}
\text{Joint Histogram} & \quad (\text{HIST}[x,y]) \\
\text{Intensities of the} & \quad \text{floating image} \quad f(x,y) \\
\text{reference image} & \quad X \\
\text{Optimum} & \quad \eta(X,Y) \\
Y & \quad \Phi(X) \
\end{align*}
\]

\[
\sigma[1] = \frac{\text{var}[f(X,Y)]}{\text{var}[f(Y)]}
\]

Joint Histogram: Statistical Dependencies \((e.g. \text{Mutual Information})\)

\[
\begin{align*}
\text{Joint Histogram} & \quad (\text{HIST}[x,y]) \\
\text{Intensities of the} & \quad \text{floating image} \quad f(x,y) \\
\text{reference image} & \quad X \\
\text{Optimum} & \quad MI(X,Y) \\
\text{Mutual Information} & \quad NMI(X,Y) = \frac{H(X,Y)}{H(X)H(Y)}
\end{align*}
\]

\[
\begin{align*}
\text{Mutual Information} & \quad MI(X,Y) = H(X) + H(Y) - H(X,Y) \\
\text{Normalized Mutual Information} & \quad NMI(X,Y) = \frac{H(X,Y)}{H(X)H(Y)}
\end{align*}
\]
Joint Histogram: Statistical Dependencies (e.g. Mutual Information)

Joint Histogram: 
\[ \text{Joint Histogram (HIST}(x,y)) \]

\[ \Phi(T_x = 3\text{mm}) \]
\[ \Phi(T_x = 5\text{mm}) \]

Optimization Issues (\(\Psi\))

**Definition:** The optimization method defines how the cost function (\(\Delta\)) 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 ($\Psi$)

- 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 ($\Psi$) (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])

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

<table>
<thead>
<tr>
<th>#</th>
<th>Authors</th>
<th>Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>[86-88]</td>
<td>F. Bookstein (general morphometry, brain, TPS)</td>
<td></td>
</tr>
<tr>
<td>[91]</td>
<td>F. Bookstein (general morphometry, brain, TPS)</td>
<td>D. Lemoine et al. (brain, Talairach Grid System)</td>
</tr>
<tr>
<td>[93]</td>
<td>F. Bookstein et al. (general morphometry, brain, TPS)</td>
<td>K. Shields et al. (carotid plaques in US)</td>
</tr>
<tr>
<td>[95]</td>
<td>G. Christensen et al. (brain, fluid model)</td>
<td>L. Collins et al. (brain, atlas based segmentation)</td>
</tr>
<tr>
<td></td>
<td>J. Gee et al. (brain, bayesian framework)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S. Sandor et al. (brain, atlas based segmentation)</td>
<td></td>
</tr>
<tr>
<td>[97]</td>
<td>P. Edwards et al. (brain, interventional imaging)</td>
<td>T. Schiemann et al. (volume interaction)</td>
</tr>
<tr>
<td>[99]</td>
<td>A. Caunce et al. (sulci shape model)</td>
<td>G. Christensen et al. (brain, homomorphism)</td>
</tr>
<tr>
<td></td>
<td>H. Chui et al. (brain cortical point)</td>
<td>L. Collins et al. (brain, atlas based segmentation)</td>
</tr>
<tr>
<td></td>
<td>H. Lester et al. (brain, fluid model)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>D. Rey et al. (brain, growth of pathologies)</td>
<td>K. Rohr et al. (TPS)</td>
</tr>
<tr>
<td></td>
<td>K. Shields et al. (carotid plaques in US)</td>
<td></td>
</tr>
</tbody>
</table>

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

Deformable registration: When?

<table>
<thead>
<tr>
<th>ONE patient</th>
<th>SEVERAL patients</th>
</tr>
</thead>
<tbody>
<tr>
<td>ONE modality</td>
<td></td>
</tr>
<tr>
<td>Registration of temporal sequences:</td>
<td>Model-based segmentation</td>
</tr>
<tr>
<td>Temporal deformation of anatomical structures (heart, chest, blood flow)</td>
<td>Building of digital atlases</td>
</tr>
<tr>
<td>Growth, Pathologies follow-up</td>
<td>Registration/matching with an anatomical atlas</td>
</tr>
<tr>
<td>Spatial normalization, study of anatomical variability</td>
<td>Human brain mapping</td>
</tr>
<tr>
<td>Correction of fMRI acquisitions</td>
<td>Anatomo-functional normalization (aid for the study of functional variability)</td>
</tr>
<tr>
<td>Constraints to reconstruction / restoration algorithms</td>
<td></td>
</tr>
<tr>
<td>Computer Assisted Surgery</td>
<td></td>
</tr>
<tr>
<td>registration between pre- and intra-operative images (e.g. MRI and Ultrasound)</td>
<td></td>
</tr>
</tbody>
</table>
Deformable Registration: which transformation?

- Non-linear dense transformation:

  Definition: The transformation can be represented as a dense deformation field: a displacement vector $\delta$ is associated to each point of the homologous structures $\Omega_s$ and $\Omega_t$:
  $$\delta: p_t = p_s + \delta(p_s)$$

- In an energetic framework, the general formulation becomes:
  $$\arg\min_{\theta \in \Theta} \mathbb{E}[\Delta(p_s + \delta_\theta(p_s), p_t)] + \mathbb{E}[\delta_\theta]$$

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

Subjects Data Base — Segmented Sulci — Registered Sulci — Statistical Model of Sulcus

- **Local Registration**
  - Hybrid Matching to Reference Sulcus and Brain
  - Probability of Sulcus X
  - Probability of Activation Y

- **Global Registration**
  - Dense Matching to Reference Brain
  - Probability of Sulcus X
  - Probability of Activation Y

- **Hybrid Registration**
  - Hybrid Matching to Reference Sulcus and Brain
  - Probability of Sulcus X
  - Probability of Activation Y
Example of Inter-Individual Registration

Before registration

After deformable registration

Averaging of 9 brains


Deformable Registration: Local, or “geometric” methods

Definition of local landmarks

Definition of a deformation model

C. Barillot, Medical Imaging II

C. Barillot, Visages U746
INSERM/INRIA, IRISA, Rennes, France
**Talairach Stereotactic Proportional Grid System**


---

**Talairach Atlas**

(C. Barillot, « Medical Imaging II »)
Probabilistic atlas based on local constraints

Inter-subjects registration of sparse data (MEG)

Statistical Shape Analysis

Synthesis

Proper mode of deformation of the right central sulcus

Segmentation of the sulci using the «Active Ribbon» Method

Brain Segmentation and Lsv computation

Initialization

C. Barillot, « Medical Imaging II »
Extraction of the local features

Linear Local Registration (LR)

29 subjects
Statistical Shape Model: Principal Component Analysis

\[ C = \frac{1}{m} \sum_{i=1}^{m} x_i \]
\[ \bar{X} = \frac{1}{m} \sum_{i=1}^{m} x_i \]

\[ x = \bar{X} + \Phi b \]

Non-Linear Local Registration (NLL):
Use of thin plate splines

\[ f(\mathbf{x}, \mathbf{y}, \mathbf{z}) = a_x x + a_y y + a_z z + \sum_{i=1}^{3210} w_i f_i(\mathbf{r} - (\mathbf{x}, \mathbf{y}, \mathbf{z})) \]
Somatotopy around the principal mode using the non-linear local method (NLL)

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):
  \[
  U(\alpha, f) = \sum |V(f(x,t) - f_{x,t})|^2 + \alpha \sum |y_i - a_i|
  \]

- Robust estimation of the deformation field:
  - Reduce the sensitivity to noise and preserve the deformation discontinuities:
  \[
  U(\alpha, \beta, f) = \sum \delta |V(f(x,t) - f_{x,t})|^2 + \phi(\delta) + \alpha \sum |y_i - a_i| + \phi(\beta)
  \]

- Adaptative multigrid algorithm:

  - Extensible to other similarity functions (e.g. fMRI registration):
Deformable Registration: Spatial Normalization

Hybrid Approach

Averaging of 18 subjects
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):

\[
U(\omega; f, \omega^*) = \sum_{s \in S} [\nabla f(s, t) \cdot \omega_s + f_s(s, t)]^2 + \alpha \sum_{s, r > \epsilon \in C} ||\omega_s - \omega_r||^2 + \alpha' \sum_{s \in \epsilon \in S} ||\omega_s - \omega_s^*||^2
\]

- Matching of homologous structures (e.g. sulci)
- Taking into account possible interruptions between sulci
Deformed central sulci (from 18 subjects)

Visualization of the cortical deformation
Cooperation between Segmentation and Registration Tasks

Cooperative scheme for Data Fusion
Model-Guided Segmentation and Labeling: Integration of fuzzy control and level sets*

- **Objective**: Segmentation of brain structures close, with similar intensities and hardly defined contours
- **Method**:
  - Statistical analysis of shape and localization of structures
  - Concurrent evolution of several level sets
- **Contribution**:
  - Integration of fuzzy control to constrain the competitive evolution of level sets
  - Utilization of a statistical shape models to define the fuzzy control variables

* C. Ciofolo, C. Barillot, IPMI 2005, ECCV 2006
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

Sulci Labeling

Source: [LeGoulher et al., 2000]
Data Fusion of Anatomical and Functional Brain Images

Deformable Registration for Anatomo-Functional Imaging

Talairach Atlas

MEG Localisations

Christian BARILLOT, Visages U746
INSERM/INRIA, IRISA, Rennes, France
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

Gaussian Ellipsoid at $3\sigma$ 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/intensity-based methods
  - Barely efficient on cortical anatomy
  - Template dependent (unless diffeomorphism)
  - Not yet real-time (Towards GPU implementation)
Deformable Registration: Limits

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

Source: [Collins et al., 1996]
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)

<table>
<thead>
<tr>
<th>MI</th>
<th>PS</th>
<th>An</th>
</tr>
</thead>
</table>

| De | RM |

C. Barillot, "Medical Imaging II"

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 thru joint observation models and numerical optimization schemes (e.g. active shape formulation)

Towards virtualization of medical imaging resources:
Share heterogeneous and distributed data and image processing tools
Sharing of medical imaging resources: Main 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 Grid 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

“Neurobase” Test Bed Architecture: Exploitation

[Diagram showing the network architecture with nodes and connections, including Le Select, IRISA, and client demo.]
NeuroBase Web Application: Query

Subject
- Age (8 bits, Analyze)
- Sex

Study
- Pathology
  - Don't use pathology to narrow search
  - Only healthy subjects
  - Subjects with pathology
  - Alzheimer's Disease
  - Parkinson's Disease
  - Amyotrophy
  - Dementia

Brain Function
- Don't use brain function to narrow search
  - Neur
  - Studies of brain function
    - motor
    - action
    - perception
    - attention
    - auditory
    - language

Data Set
- Format
  - DynamicImage
  - OriginalPET
  - RegistrationDataset
  - MRVolumetricDataset
- Origin
  - Brain
  - BrainMatterOfBrain
  - GreyMatterOfBrain
  - CerebralVascularFluidOfBrain
- Content
  - Active

Result's Display
- Display's choice
  - Show all columns
  - Display only the most important column
- Search

Heterogeneous and Distributed Workflow/DataFlow

Rennes
- Head MRI (8 bits, Analyze)
- Brain Mask BET/FSL
- Classified Volume (8 bits, GIS)

Grenoble
- Head MRI (8 bits, Analyze)
- Brain Mask (8 bits, Analyze)
- Classified Volume (8 bits, GIS)

Data Flow
- Restoration VISTAL
- Classification GM/WM VISTAL
- 2D/3D Display (Client BrainVisa/Anatomist)

Calculated Volume (8 bits, GIS)
NeuroBase WebApp:
Data Flow Results

Some references:
Thesis or Books on data fusion and registration, and on general aspects


C. Barillot, « Medical Imaging II »
### Review Papers


### Research Papers on deformable registration (I)

Research Papers on deformable registration (2)


Research Papers on deformable registration (3)

Research Papers on deformable registration (4)


Other related research paper