Registration and Its Medical Applications

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Syllabus

- Registration problem
  - Definitions, examples
  - Main components
- Medical image registration
  - Modalities (X-ray, US, MR, CT, PET, SPECT)
  - Applications
- Registration methods
  - Point-based methods
  - Surface fitting methods
  - Automatic methods
  - Non-linear registration

Image Registration

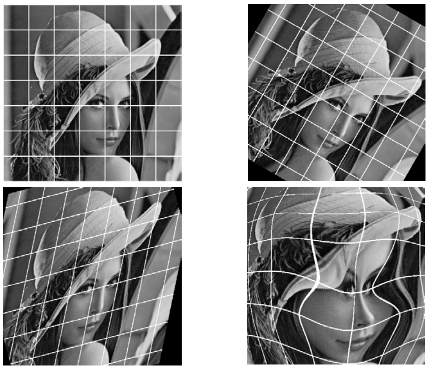
Task:

To find geometrical correspondence between images.

Terms:

- *image registration*
- *image matching*
- *image fusion*

Image Transformations

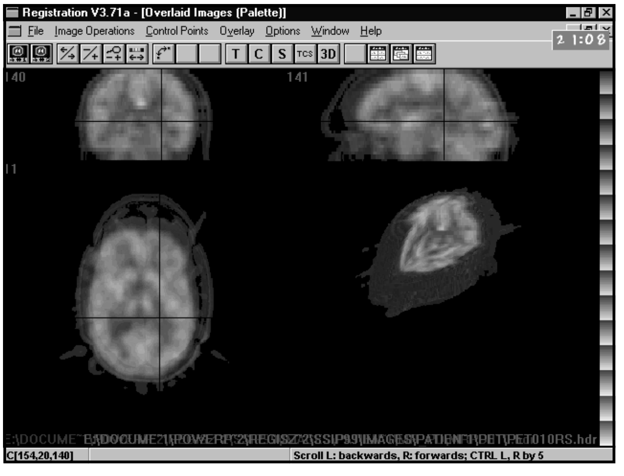


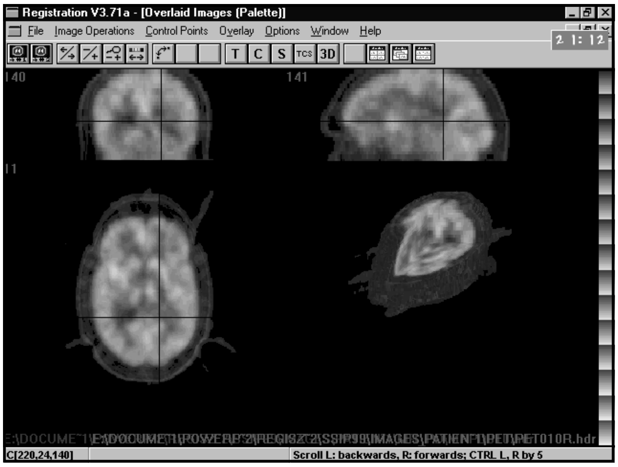
Registration (General)

Task:

Combine (spatial) *information contents* coming from the same or different *sources*.

- Images,
- 2-D or 3-D models of objects,
- Spatial positions.





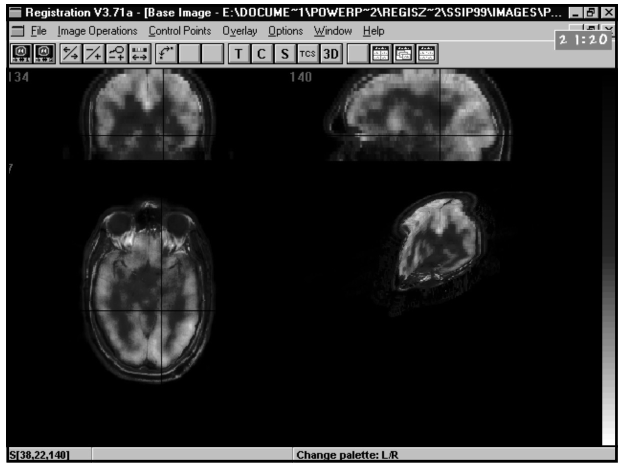
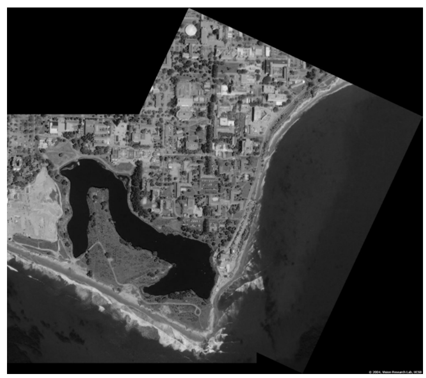


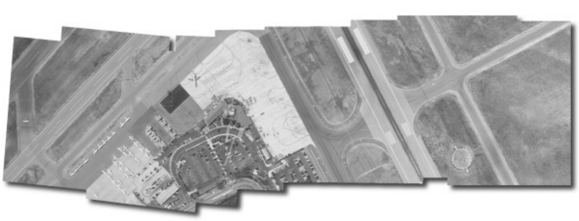
Image Mosaicking

Vision Research Lab, UCSB



Vision Research Lab, UCSB

Image Mosaicking



Vision Research Lab, UCSB

Image Mosaicking

A.A. Goshtasby

Image Mosaicking

A.A. Goshtasby

Amazonian Deforestation Progress

1992 1994

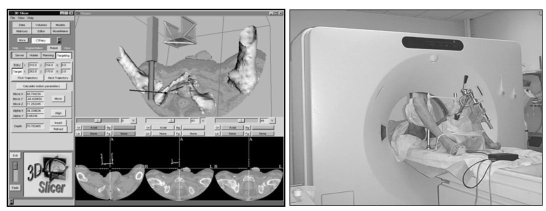
Vision Research Lab, UCSB

Amazonian Deforestation Progress

Vision Research Lab, UCSB

Surgery Planning and Execution

- Model - Modality
- Modality - Patient



Prostate biopsy project, Johns Hopkins University, Baltimore, MD, USA

Major Research Areas

- Computer vision and pattern recognition
  - segmentation, motion tracking, character recognition
- Medical image analysis
  - tumor detection, disease localization, classification of microscopic images
- Remotely sensed data processing
  - geology, agriculture, oceanography, oil and mineral exploration, forestry
- ...

Variations Between Images

- Corrected distortions (easier)
  - Distortion which can be modeled (e.g. geometric differences due to viewpoint changes).
- Uncorrected distortions (medium)
  - Distortions which are difficult to model (e.g. lighting and atmospheric conditions, shadows).
- Variations of interest (harder)
  - Differences we would like to detect (e.g. Object movements or growth).

Main Components

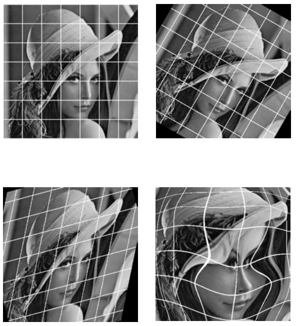
- Search space
  - Type of geometric transformation.
- Feature space
  - What features to use to find the optimal transformation.
- Similarity measure
  - Defines how similar two images are.
- Search strategy
  - How to find the global optimum of the similarity measure.

Search Space

Original image

Rigid-body transformation

2D: 3 parameters
3D: 6 parameters



Affine transformation

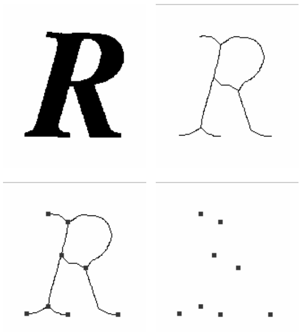
2D: 6 parameters
3D: 12 parameters

Nonlinear transformation

2D,3D: as many parameters as desired.

Feature Space

- Goal:
  - Reduce amount of data,
  - by extracting relevant features.
- Features:
  - Geometric (e.g. points, edges, surfaces).
  - Image intensities (e.g. the whole image).

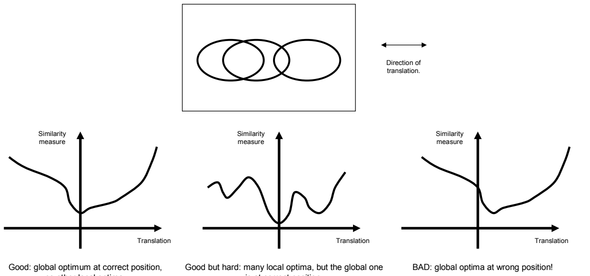


Similarity Measure

- Geometric features
  - Distance measures (e.g. minimization of Euclidean distance).
- Image intensity-based
  - Based on intensity differences (e.g. absolute/squared sum of intensity differences, sign changes of the difference image).
  - Correlation-based (cross-correlation, correlation coefficient).
  - Based on the co-occurrence matrix of the image intensities (e.g. joint entropy, mutual information).

Similarity Measure

- Example: 1D transformation



Good: global optimum at correct position, no other local optima.

Good but hard: many local optima, but the global one is at correct position.

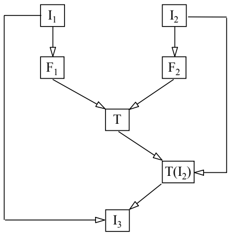
BAD: global optima at wrong position!

Search Strategy

- Direct methods
- ‘Coarse to fine’ search
- Multiresolution pyramid
- Dinamic programming methods
- Relaxation methods
- Heuristic search, genetic algorithms
- ...

Optimization is a bigger research field than registration itself!

Registration Process



Feature extraction

Determining the optimal transformation

Applying the transformation

Image fusion

Medical Image Registration

Matching all the data available for a patient

- provides better diagnostic capability,
- better understanding of data,
- improves surgical and therapy planning and evaluation.

Medical Image Registration

Potential medical applications

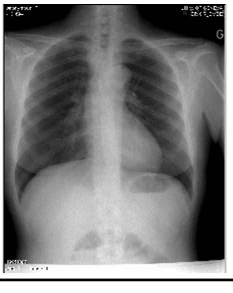
- Combining information from multiple imaging modalities (e.g., functional information to anatomy).
- Monitoring changes in size, shape, or image intensity over time intervals (few seconds to years).
- Relating preoperative images and surgical plans to the physical reality of the patient (image-guided surgery, treatment suite during radiotherapy).
- Relating an individual's anatomy to a standardized atlas.

Imaging Modalities

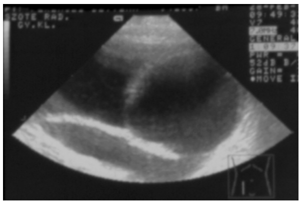
- 2D imaging
  - Anatomical
    - X-ray
    - US
  - Functional
    - Gamma camera
- 3D imaging
  - Anatomical
    - MR
    - CT
  - Functional
    - SPECT
    - PET
    - fMRI

2D Imaging

X-ray

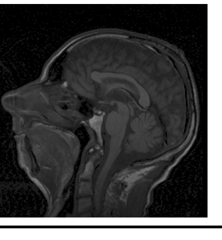


Ultrasound

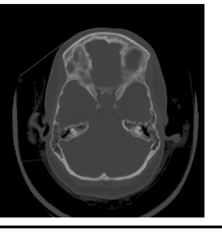


3D Anatomical Imaging

Magnetic Resonance
256x256

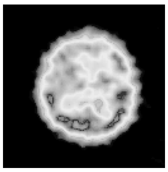


Computed Tomography
512x512

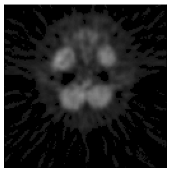


3D Functional Imaging

SPECT
(*Single Photon Emission Computed Tomography*)
64x64



PET
(*Positron Emission Tomography*)
128x128



3D Functional Imaging

fMRI
(*functional Magnetic Resonance*)
256x256

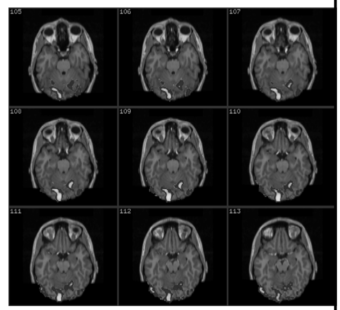
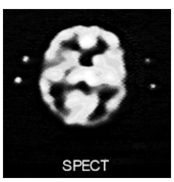


Image from http://www.fmrib.ox.ac.uk/fmri_intro/brief.html

Type of Features

- Extrinsic (artificial)
  - Stereotactic frames
  - Head and dental fixation devices
  - Skin markers

  Accurate, uncomfortable for the patient, non-retrospective.

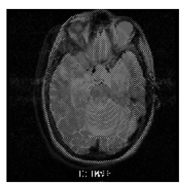


- Intrinsic
  - Anatomic areas (points, surfaces)
  - Geometric features
  - Image intensities

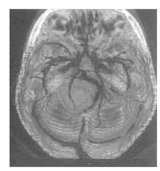
  Accurate, comfortable, retrospective.

Modalities

- Unimodality
  - Time series
  - Different protocol settings
  - Atlas matching

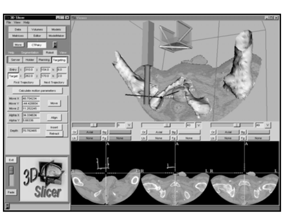


- Multimodality
  - Complementary image contents



Modalities

- Model - Modality



- Modality - Patient

Prostate biopsy project, Johns Hopkins University, Baltimore, MD, USA

Image Sources

- Intrasubject
  - Same patient.
- Intersubject
  - Different people.
- Atlas matching
  - Different people, to get „average” information.

Interactivity

- Manual
  Decent visualization software is necessary. Labour intensive.
- Semi-automatic (interactive)
  Reliable, fast, but trained user might be required.
  - User initializes (e.g. point selection, segmentation).
  - User decides (accept/reject).
  - Combined together.
- Automatic
  - Easy to use.
  - Usually accurate, but visual inspection is necessary.
  - Can take a lot of time (especially in nonlinear cases).

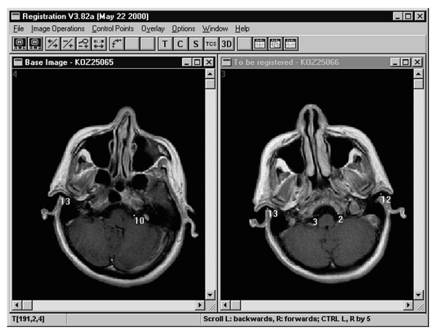
Registration Algorithms

- Point-based methods,
  - Reliable, fast, but trained user might be required.
- Contour/surface fitting methods,
- Automatic volume fitting based on voxel similarity measures.

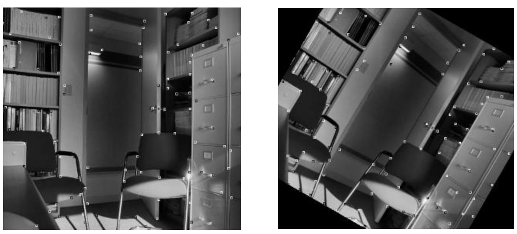
Point Pair Selection

- Interactive
  - Selection of point pairs
    - Might require trained user,
    - Can be hard (e.g. in 3D), or even impossible (MR – SPECT TRODAT),
    - Might take lot of time (few minutes – 10-30 minutes).
- Automatic
  - Feature extraction (e.g. corner points).
  - Number of points can be different.
  - Pairing is to be solved!

Interactive Point Pair Selection



Automatic Point Selection



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Point-Based Methods

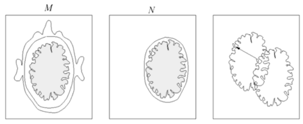
- Rigid-body, similarity transformation
  - SVD, unit quaternions, iterative search.
- Affine transformation
  - Least squares, SVD.
- Projective
  - Least squares.
- Polinomial transformations
  - 2nd, 3rd, n-th order.
- Nonlinear transformations
  - Thin-plate spline, B-Spline, multiquadrics, RBF, etc.

Registration Algorithms

- Point-based methods,
- Contour/surface fitting methods,
- Automatic volume fitting based on voxel similarity measures.

Contour/Surface Fitting

- Extraction of same contours/surfaces
- Contour/surface distance definition
- Optimization (iterative method)
- Outliers problem



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Distance Definition

- Point-based $D_P(T) = \sum_{i=1}^{K} \| x_i - T(y_i) \|^2$

- Contour/surface $D_S(T) = \sqrt{\sum_{i=1}^{K} \| x_i - P(T(Y), x_i) \|^2}$
  - Closest point in the transformed Y point set.
  - Closest point in the triangulated surface mesh of the transformed Y point set.
  - Etc.

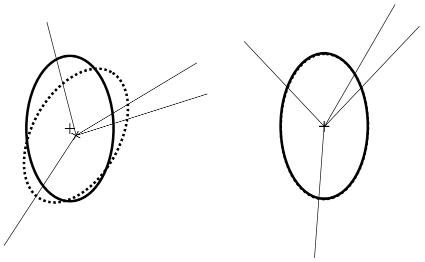
Contour/Surface Methods

- Head-hat (Pelizzari, 1989)
- Hierarchical Chamfer Matching (Borgefors, Jiang, 1992)
- Iterative Closest Point (Besl, McKay, 1992)

Head-Hat Method (Pelizzari)

- MR-PET registration
- Skin surface, semi-automatic segmentation
- 20 minutes segmentation, 5 sec registration
- For non-symmetric spherical objects (e.g., head, heart)
  - Surface of the finer resolution image: stack of disks.
  - Surface of the coarser resolution image: set of points.
  - Matching of the centroids (translation).
  - Distance: squared sum of the distance of the points and the intersection of the disks and the line defined by the centroid and the given point.
  - Optimization: Powell's method.

Head-Hat Method (Pelizzari)



Contour/Surface Methods

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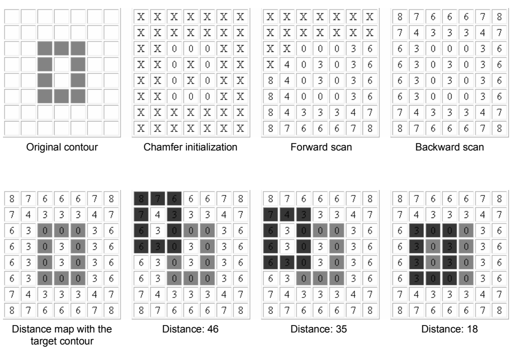
Chamfer Matching

- Determination of the contours/surfaces.
- Distance map calculation in the base image.
  - For each voxel, the distance to the closest contour/surface point is pre-calculated.
- Distance: sum or squared sum of the distance values at the transformed floating contour/surface points.

Chamfer Matching



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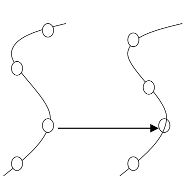
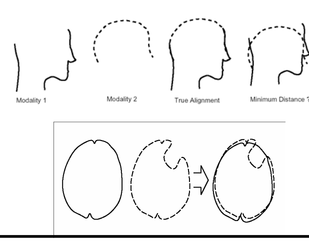
Iterative Closest Point

- Originally: Sensed – Model data matching
  - Sensed data representation: point set
  - Model data representation: point set, line segment set, triangulated surface, parametric surface, etc.
- Iterations consist of two steps
  - Determination of point pairs
  - Point-based registration
- Avoid local minima
  - Start the algorithm multiple times with a different estimate of the rotation alignment.



Outliers Problem

- Remove non-overlapping parts
  - Manually
  - RANSAC, etc.



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Registration Algorithms

- Point-based methods,
- Contour/surface fitting methods,
- Automatic volume fitting based on voxel similarity measures.
  - Easy to use.
  - Usually accurate, but visual inspection is necessary.
  - Can take a lot of time (especially in nonlinear cases).

Intensity Differences

$$\mathrm{SSD} = \frac{1}{N} \sum_{x_A \in \Omega_A} \left| A(x_A) - B^T(x_A) \right|^2 , \qquad \mathrm{SAD} = \frac{1}{N} \sum_{x_A \in \Omega_A} \left| A(x_A) - B^T(x_A) \right|$$

- Optimal when the noise is Gaussian.
  - For unimodality registration.
  - Unimodality problems
    - Noise is not Gaussian in MR.
    - Contrast agents can cause big intesity differences.

Correlation Techniques

$$\mathrm{C} = \frac{1}{N} \sum_{x_A \in \Omega^T_{A,B}} A(x_A) \cdot B^T(x_A) \qquad \mathrm{CC} = \frac{\sum_{x_A \in \Omega_A} \left(A(x_A) - \overline{A} \right) \cdot \left(B^T(x_A) - \overline{B} \right)}{\sqrt{\sum_{x_A \in \Omega_A} \left(A(x_A) - \overline{A} \right)^2 \cdot \sum_{x_A \in \Omega_A} \left(B^T(x_A) - \overline{B} \right)^2}}$$

- Optimal when the relationship is linear between intensities of the images.
  - For unimodality registration.

Partitioned Image Uniformity

$$\mathrm{PIU} = \sum_a \frac{\mathrm{n_a}}{\mathrm{N}} \cdot \frac{\sigma(a)}{\mu(a)} \qquad n_a = \sum_{\Omega_a} 1 \qquad \mu(a) = \frac{1}{n_a} \cdot \sum_{x_A \in \Omega_a} B^T(x_A) \qquad \sigma(a) = \sum_{x_A \in \Omega_a} \left(B^T(x_A) - \mu(a) \right)^2$$

- Assumed: an intensity value describes a tissue type well in both images.
- For MR-PET registration (Woods, 1992)
  - Remove parts outside of brain from PET.
  - Transform MR intensity scale to 256 values.
  - Maximizes the uniformity of the intensities from PET paired with intensities of MR.

Mutual Information

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

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

H(X), H(Y): entropy

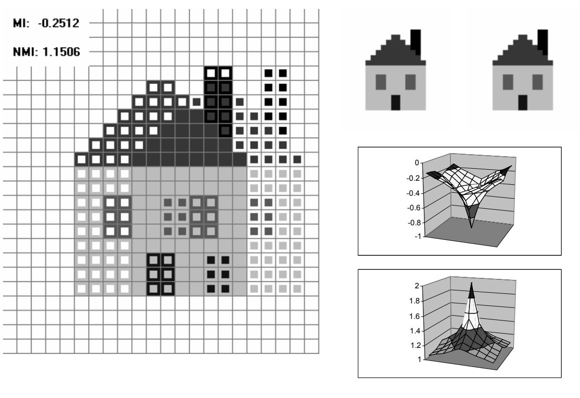
H(X,Y): joint entropy

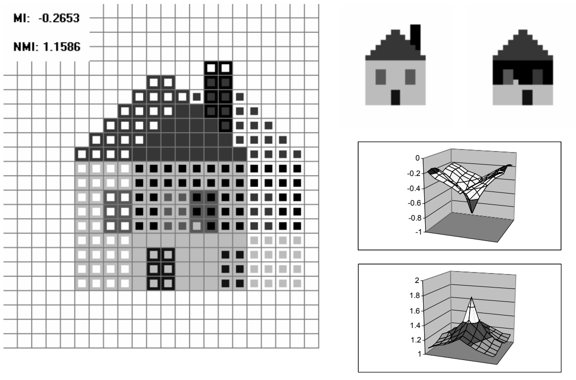
$$\mathrm{H(A)} = -\sum_a p_A(a) \cdot \log p_A(a)$$

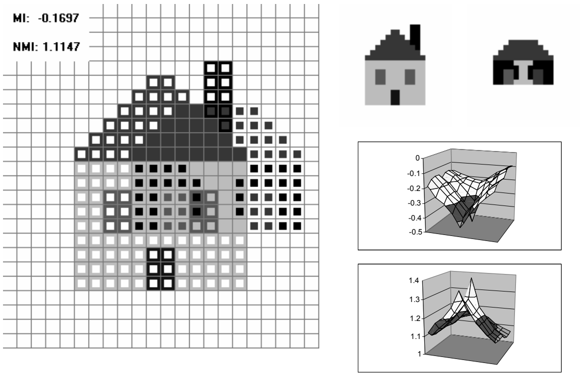
$$\mathrm{H(B^T)} = -\sum_a p_{B^T}(a) \cdot \log p_{B^T}(a)$$

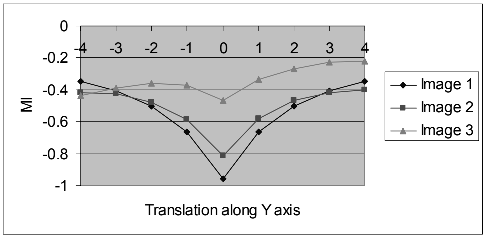
$$\mathrm{H(A,B^T)} = -\sum_a \sum_b p_{AB^T}(a,b) \cdot \log p_{AB^T}(a,b)$$

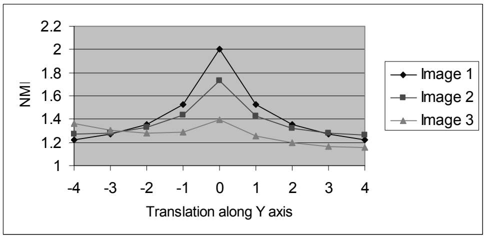
(Collignon, Viola 1995)







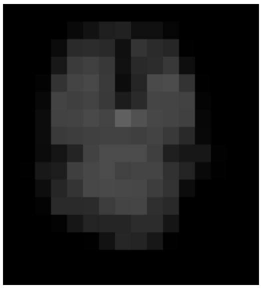




Need for Non-linearity

- Tissue deformations due to
  - Interventions,
  - Changes over time,
  - Respiration, heart beat,
  - Anatomial variability across individuals.
- Methods
  - Polinomials
  - Splines (TPS, B-Splines, multiquadrics, etc.)
  - Elastic, Fluid, Diffusion, Curvature registration
  - FEM and mechanical models
  - Optical flow

Non-linear Example



Displacement Field

- u(*x,y,z*)
  - For each voxel a vector is assigned.
    - Lagrangian reference frame: where the voxel moves to.
    - Eulerian reference frame: where the voxel value comes from.
- Need for regularization!
  - Constraints on the displacement field.

Non-linear Methods

- Polinomials
  - Lines mapped to 2nd, 3rd, n-th order polinomials.
  - Problems: Global shape changes, oscillations.
- Splines
  - Control point pairs
    - Identified landmarks or regular mesh.
  - Interpolating or approximating at control points.
  - Result: Smoothly varying displacement field.
  - Methods
    - Thin-plate splines: Additional constraints can be added (rigid bodies, degree of approximation), but control point change is global.
    - B-Splines: Local change, computationally efficient. Needs regular mesh.

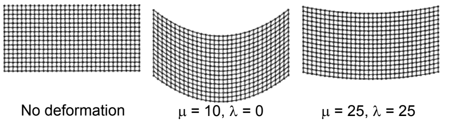
Elastic Registration

- Stretching the image as it was from an elastic material, e.g., rubber
  - Broit (1981), Bajcsy (1989).
  - Internal force (behaviour of the elastic body)
    - Lamé's elasticity constants: μ, λ
    - Young's modulus (E_1) and Poisson's ratio (E_2)
  - External force (acts on the elastic body)
    - E.g, gradient of a similarity measure, distance between curves and surfaces (f).
  - Optimal deformation: at equilibrium.

$$\mu\nabla^2 \mathrm{u}(x,y,z) + (\lambda+\mu)\nabla(\nabla\cdot \mathrm{u}(x,y,z)) + \mathrm{f}(x,y,z) = 0$$

Elastic Registration

- Implicitly assumes small displacement changes!



No deformation μ = 10, λ = 0 μ = 25, λ = 25

- Numerical methods for solving the PDE
  - Finite differences
  - Successive over relaxation (SOR)
- Extensions
  - Spatially varying elasticity parameters (Davatzikos)

Fluid Registration

- Deform the image over time as it was a viscous, thick fluid
  - Christensen (1994)
  - Can deform any image to another (sharing the same intensity range).
  - Characteristic comparison
    - Elastic model: spatial smoothing of the displacement field (u).
    - Fluid model: spatial smoothing of the velocity field (v).

$$\mu\nabla^2 \mathrm{v}(x,y,z) + (\lambda+\mu)\nabla(\nabla\cdot \mathrm{v}(x,y,z)) + \mathrm{f}(x,y,z) = 0$$

Fluid Registration

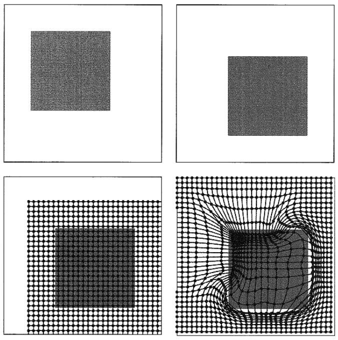
- Numerical methods for solving the PDE
  - Successive over relaxation (Christensen) – slow!
  - Convolution filter (Bro-Nielsen) – for constant viscosity
- Extensions
  - Viscousity of the fluid varies spatially (Lester)

Image from Bro-Nielsen (http://www.mortenbronielsen.net/phd_proj_register.htm).

Deformation Field Differences

Reference

Template



Curvature registration

Fluid registration

Image from Jan Modersitzki

Insight Toolkit (ITK)

- Toolkit for image processing, segmentation and registration
  - C++
  - Open-source, cross platform
  - Generic programming via templates
  - Wrappers for Tcl/Tk, Java, Python, interface to VTK
  - Registration framework
    - Image registration, multiresolution registration, PDE-based registration, and FEM registration.
  - FEM framework
    - Mesh definition, loads, boundary conditions.
  - I/O Framework
    - DICOM parser
- Website: http://www.itk.org

Selected Surveys and Books

- General

  - Brown, L.G.: A survey of image registration techniques. ACM Computing Surveys 24 (1992) 325-376
  - Modersitzki, J.: Numerical Methods for Image Registration. Oxford University Press (2004)
  - Goshtasby, A.A.: 2-D and 3-D Image Registration for Medical, Remote Sensing, and Industrial Applications. Wiley and Sons (2005)

- Medical

  - Maintz, J.B.A., Viergever, M.A.: A survey of medical image registration. Medical Image Analysis 2 (1998) 1-36
  - Studholme, C.: Measures of 3D Medical Image Alignment. PhD Thesis, University of London (1997)
  - Hajnal, J.V., Hill, D.L.G., Hawkes, D.J. (eds.): Medical Image Registration. CRC Press (2001)

- Internet
  - http://vision.ece.ucsb.edu/registration/imreg/
  - http://www.imgfsr.com/