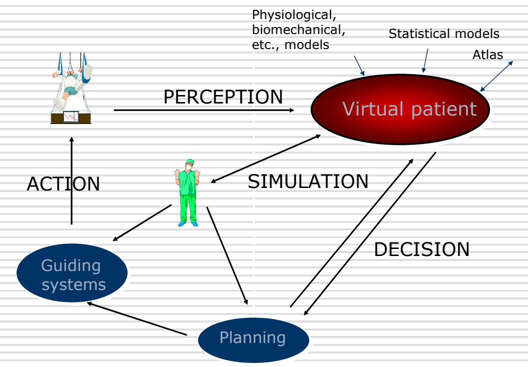
Registration and data fusion

Problem, Methods, Examples

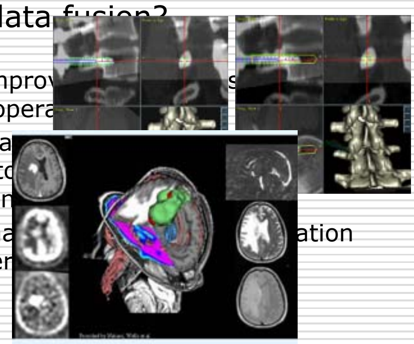


Medical images

- Pre-op/intra-op/post-op
- 2D/2.5D/3D/3D+t
- Anatomical/functional
- Based on different physical phenomena:
  - X-rays: CT, radiographs, etc.
  - Magnetic fields: MRI, fMRI, MEG, etc.
  - Ultrasounds
  - Radioactivity: SPECT, PET, etc.
  - Light propagation: endoscopy, microscopy, etc.
  - Etc.
- Each modality brings its own type of information

Why data fusion?

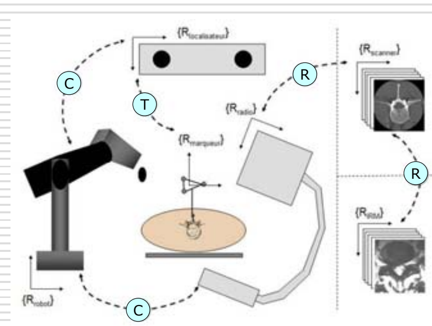
- To improv… s pre-opera…
- To tra… and to… and in…
- To ma… ation easier…



Definitions

- Image fusion = image registration = image matching
- Let consider two reference systems R_A and R_B in which common information are represented: one is looking for $T_A{}^B$ that allows mapping information from one referential to the other one
- Data may come from: the patient (2D, 3D, 3D+t), another patient (atlas), a population of patients

Integration of multi-modal informations



Problem

- Calibration/registration/tracking
- The registration problem
  - R_A and R_B : two reference systems associated to two « modalities » A and B
  - F_A and F_B : corresponding informations represented in R_A and R_B
  - T_A^B :a transformation relating R_A and R_B
  - s : a similarity fonction between two types of information (or d a distance fonction)
  - ➢ We are looking for the value of T_A^B that maximizes the similarity between T_A^B (F_A) and F_B

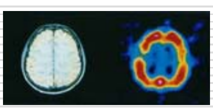
$$T_A^B = \arg\max s\,(T_A^B(F_A), F_B)$$

Several instances of the registration problem

- Monomodal versus multimodal
- Intra-patient versus inter-patient(s)
- Dimensionality
  - 2D/2D, 2D/3D, multi-slices2D/3D, 3D/3D, 3D/4D, etc.
- Nature of the transform T_A^B
  - Rigid: translation+rotation
  - Non rigid: translation + rotation + deformation

Direct/non direct

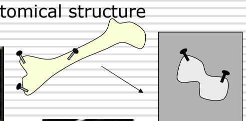
- Direct registration:
  - It exists corresponding information F_A and F_B visible both in modalities A and B
- Non direct registration:
  - Adding corresponding extra-information F_A and F_B both visible in modalities A and B
  - Adding an extra-modality C (ex. SPECT/MRI-CT registration using a surface sensor)



Non direct registration using artificial fiducials

- Invasive fiducials (pins, seeds, frame)
  - (Light) infectious risks and potential modification of the anatomical structure





CT

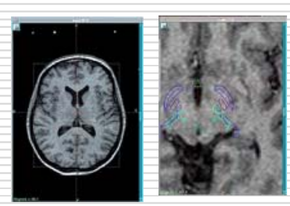
- Surface fiducials
  - May move



Direct registration using natural fiducials

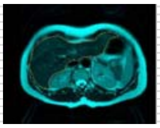
Example: elastic registration of Schaltenbrandt atlas to MRI (via the Talairach grid)

Paired features



Direct anatomical registration

- Using segmented data (feature-based methods)




- Using « raw » data (intensity-based methods)

Which method?

- How complex is the transform to be encoded?
- Which types of information have to be registered?
- What similarity function is to chosen?
- How is the optimization performed ?

Encoding the transform

- Rigid: 3 rotations+3 translations
- Rigid + scaling: 6+1 (isotropic) or 6+3 (non isotropic)
- Affine: 12 (rigid + 3scaling + 3shear)
- Non rigid complex (rigid + deformation field U)

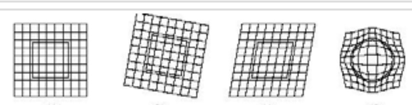


Figure 1: Example of different types of transformations of a square: (a) identity transformation, (b) rigid transformation, (c) affine transformation, and (d) non-rigid transformation.

Affine transform

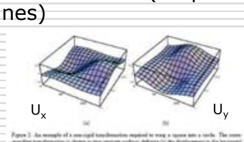
- Preserves straight lines and parallelism
- $X' = T_{shear} * T_{scale} * T_{rigid} . X$

$$T_{shear} = \begin{bmatrix} 1 & s_{yx} & s_{zx} & 0 \\ -s_{yx} & 1 & s_{zy} & 0 \\ -s_{zx} & -s_{zy} & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad T_{scale} = \begin{bmatrix} s_x & 0 & 0 & 0 \\ 0 & s_y & 0 & 0 \\ 0 & 0 & s_z & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

- In general, real anatomical deformations are more complex

More complex transforms

- Polynomials encoding U
- Decomposition using wavelets or trigonometric functions
- Splines functions (B-splines or thin-plate splines)



Splines encoding a 2D deformation mapping a square to a circle

- Statistical deformations
- Dense deformation fields

Deformation based on physical models

- Elastic deformation: pionneer paper [Bajcsy89] – elastic registration of brain (PhD Broit1981)

$$\mu\nabla^2 U(x,y,z) + (\lambda+\mu)\nabla(\nabla.U(x,y,z)) + f(x,y,z) = 0$$

- Fluid
- Finite elements: i.e. [Alterovitz06] – registration of segmented prostate on MRI
  - 2D MEF prostate model split into two zones
  - Identification of model parameters, applied forces and transform

Which information type (F_A and F_B)?

- Gray levels
- Points
- Lines
  - Retroprojection lines (2D/3D)
  - Crest lines
  - Specific anatomical structures (e.g. blood vessels)
- Surfaces
- ➢ Potentially requires pre-processing or segmentation

[G.Subsol]

Which similarity function?

- The case of point matching
- The case of surface registration
- The case of image-based registration
  - Mono-modal
  - Multi-modal

Paired points 3D/3D rigid

- Procrustes problem
- 2 sets of N paired points $\{a_i\}$ and $\{b_i\}$ (artificial features or anatomical landmarks) given in R_A and R_B
- Looking for T_A^B minimizing FRE (least-square minimization)

$$FRE = \sum_{i=1}^{N} \left\| T_A^{B}(a_i) - b_i \right\|^2$$

- In 3D, $N \geq 3$

Arun method (direct)

- Looking for R and t such as : $b_i = R*a_i + t$
- Let define $a_i' = a_i - a_i^{average}$ et $b_i' = b_i - b_i^{average}$
- $K=A^tB$ (correlation matrix relating a_i' and b_i') $= UDV^t$ (SVD), U and V orthonormals, V diagonal
- $R = V\Delta U^t$ where $\Delta = diag(1,1, det(VU^t))$
- $t = b_i^{average} - R*a_i^{average}$

Point matching example

- Example: ESAOTE Virtual Navigator™
- Rigid registration of (3 to 10) external markers or internal anatomical landmarks

Pros/cons

- Advantages
  - Fast
  - Simple
- Drawbacks
  - Identification of anatomical fiducials is highly operator-dependant
  - Precision directly related to point definition accuracy
- Often used as an initialization method for more complex registration

Surface registration

- N points $\{a_i\}$ and a surface B (defined by points, triangles, implicit surfaces, or etc.) obtained through image segmentation or directly using a suitable sensor
- Looking for T_A^B which minimizes (least squares) $d(T_A^B)$

$$d(T_A^B) = \frac{1}{N}\sum_{i=1}^{N}\left|T_A^B(a_i) - b_i\right|^2$$

where b_i is a_i's closest point on B

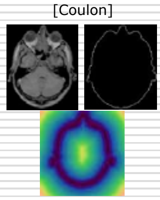
- Existing methods:
  - « Head and hat »
  - Methods using pre-computed distance maps
  - « Hybrid » ICP method

« Head and hat » [Pelizzari]

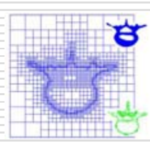
- A stack of segmented contours (head)
- A set of points to register (hat)
- $d(a_i, B) = d(a_i, b_i)$ where b_i is a_i's closest point of B on a line connecting a_i to the contour center of gravity
- Optimization using Powell algorithm
- ➢ Improvements in distance computation (precision, speed)
- ➢ Development of distance maps (« around » B)

Distance maps

[Coulon]



- Uniform maps (champfer distance [Borgefors84])



- Hierarchical maps (octree-spline [Lavallée92])

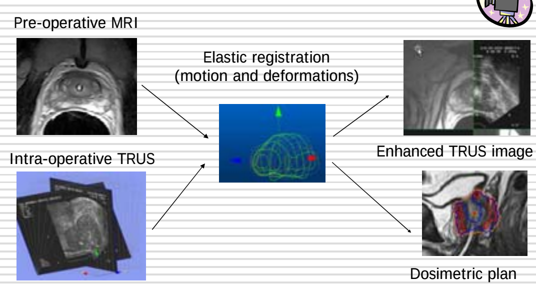
Iterative Closest Point (ICP) [McKay92]

- In between paired point matching and surface matching
- Algorithm:
  1) For each point a_i, compute the closest point b_i on B
  2) Determine T_A^B using paired point matching of a_i and b_i
  3) Apply T_A^B to a_i points
  4) While not finished go back to 1)
- Implemented for different surface representations (points, triangles, splines, implicit surfaces, etc.)
- Possible improvement by a local search of closest points using the previous iteration

Surface registration example: MRI-enhanced brachytherapy

- Prostate apex and base segmentation for dose planning is difficult on TRUS images
- Supposed bias: under-estimate of prostate volume
- Question: under-dosage ?
- Solution: « Bring » the MR data in the OR through surface elastic registration to augment TRUS images

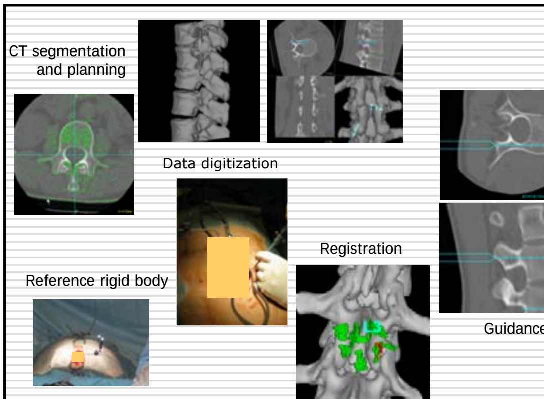
Surface registration



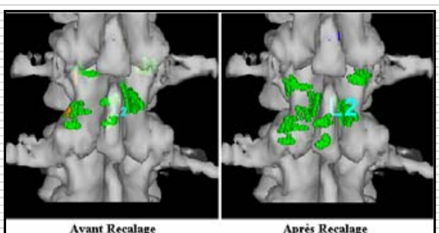
[Urology Dept (Pr Descotes) – Radiotherapy Dept (Pr Bolla) in Grenoble University Hospital – TIMC]

Spine (CT navigation)

- Pre-operative CT
- Vertebra segmentation for 3D model
- Planning
- Intra-operative points collected on the spine
  - A few landmarks (> initial attitude)
  - Random surface points
- Automatic registration to CT
- Guidance through navigation



Data registration



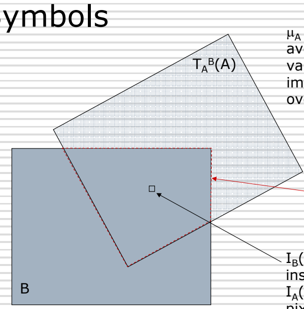
Before registration — After registration

Segmentation-less registration

= registration using an image similarity measure

- Hypothesis:
  - It exists a relationship between pixels values of a same structure in A and B
    - (identity, linear, fonctional, probabilistic, etc.)
  - The similarity is maximal when images are registered
- Different measures for mono- or multi-modal

Symbols



μ_A and μ_B (resp. σ_A et σ_B): average (resp. standard dev.) values of grey levels inside images A and B (in the overlapping zone)

Overlapping zone

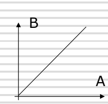
$I_B(p)$: intensity of pixel p inside image B

$I_A(T_A^B(p))$: intensity of pixel p inside image A transformed by T_A^B

Mono-modal

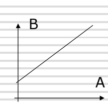
- Sum of Squared Differences (SSD)
  - Gaussian noise difference of images

$$SSD = \frac{1}{N}\sum_{i=1}^{N}(I_A(T_A^B(p_i)) - I_B(p_i))^2$$



- Normalized Cross Correlation (NCC)
  - For instance for CT acquisitions with different windows of gray levels

$$NCC = \frac{\sum (I_A(T_A^B(p)) - \mu_A)(I_B(p) - \mu_B)}{\sqrt{(\sum (I_A(T_A^B(p)) - \mu_A)^2)(\sum (I_B(p) - \mu_B)^2)}}$$



Multi-modal

- The relation between the images is unknown (fonctional, statistical relationship)
- Other measures:
  - Correlation ratio [Roche98] or PIU* [Woods93] – its exists s fonctional relating grey levels in A and B

$$CR(B|A) = 1 - \frac{1}{N\sigma^2}\sum_i N_i \sigma_i^2 \qquad PIU_B = \sum_a \frac{n_a}{N}\frac{\sigma_B(a)}{\mu_B(a)}$$

  - Measures based in information theory (entropy concept)

*partitioned intensity uniformity

Information theory

- Amount of information in a message:
  - [Hartley1928] H=nlog(s) for n symbols of s possible values – all symbols have equal probabilities
  - [Shannon1948]: introduces the concept of entropy (where p_i is the probability of event e_i)

$$\sum_i p_i \log(1/p_i) = -\sum_i p_i \log(p_i)$$

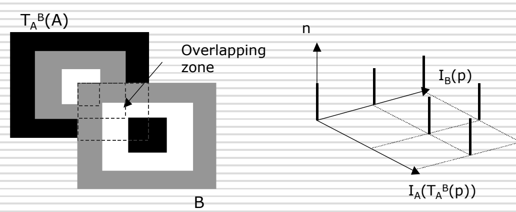
- Characterizes the amount of information carried by an event (a message for instance) or the event uncertainty

Example

- Vocabulary of a 1-year old baby:
  - Dad' (p=0.2), Mom' (0.35), Cat (0.2), oh (0.25)
  - Entropy = 1.96
- A few months later:
  - Dad' (0.05), Mom' (0.05), train (0.02), cat (0.02), car (0.02), tv (0.02), no! (0.8)
  - Entropy = 1.25
  - Less uncertainty on the next word to be pronounced (most likely « no! »)

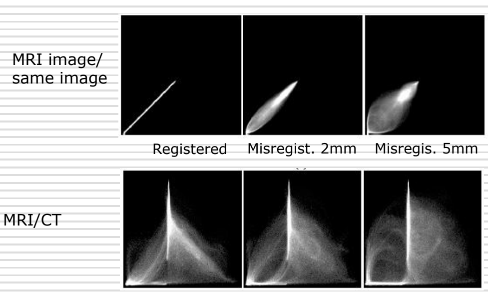
Joint histogram [Hill94]

- « Feature space »



- Probability distribution of grey levels (a,b)

Exemples from [Hill94]



Measures based on HJ

- Joint entropy [Collignon, Studholme]

$$H(A,B) = -\sum_{a,b} p(a,b)\log p(a,b)$$

- Registration through H minimization
- Mutual Information (to be maximized)

$$MI(A,B) = H(A) + H(B) - H(A,B)$$

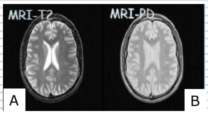
- Normalized Mutual Information

$$NMI = \frac{H(A)+H(B)}{H(A,B)}$$

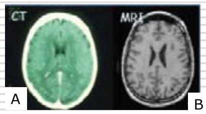
- Etc.

CR versus « entropy & co »

- CR requires the existence of a functional f« $I_B=f(I_A)$ »

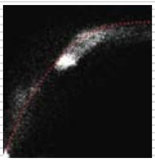


A B



A B

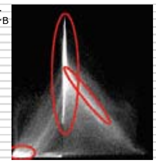
I_B



I_A

[images from Barillot]

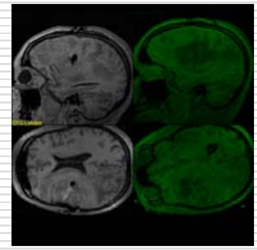
I_B



I_A

Example 1: 3D/3D affine registration

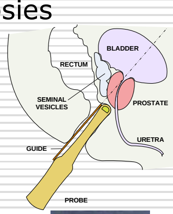
- Extensive use of such methods for « head » applications
- CT/IRM/PET…
- Example: IRM(t_1)/IRM(t_2) using NMI



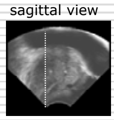
From www.image-registration.com

Example 2: Prostate biopsies

- Purpose
  - Prostate cancer detection
  - Indicated for patients with high PSA levels
- Biopsy needle guidance
  - Endorectal 2D ultrasound (US) guidance
  - Needle guide attached to probe
  - Needle trajectory in sagittal US image
  - Most tumors are isoechogenic
  - Systematic sampling (e.g. 12-core)
- Issues
  - 2D guidance for a complex 3D problem
  - Prostate moves and gets deformed with probe movements



sagittal view



Example 2 : Computer-assisted prostate biopsies

- Objectives:
  - To localize precisely biopsy samples in the gland
  - To guide a biopsy toward a precise location (e.g. from spectro-MRI)
- Problem: the prostate significantly moves and deforms during prostate biopsy series due to the TRUS probe motion

[TIMC – La Pitié Salpétrière – KOELIS – CHU de Grenoble]

Real-time registration: prostate biopsy [Baumann, Mozer, Troccaz]

- 3D US
- Construct a panorama volume (3 volumes registered)
- Registration of intra-operative volumes
  - Rigid plus elastic registration
  - Image-based (CR and SSD), multi-resolution
  - Use of kinematic model of probe movement
  - Use a model of probe related deformations
- Very good results on patient data (more than 90 patients included)

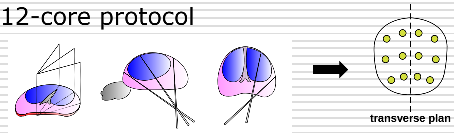
Registration results

- 12 patients/237 registrations
- « Gold standard »: calcification or needles when visible

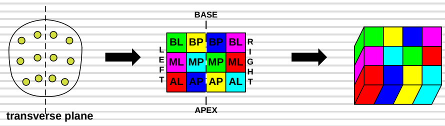
	result	pairs
Registration success	96.7%	237
Average computation time	6.5 s	237
Angular precision ϵ_A (reproducibility, r.m.s.)	1.75 deg	229
Euclidean precision ϵ_E (reproducibility, r.m.s.)	0.62 mm	229
Needle trajectory reconstruction (r.m.s.)	4.72 deg	10
Needle trajectory reconstruction (max)	10.04 deg	10
Calcification reconstruction (r.m.s.)	1.41 mm	189
Calcification reconstruction (max)	3.84 mm	189

Clinical accuracy evaluation

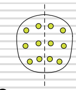
- 12-core protocol



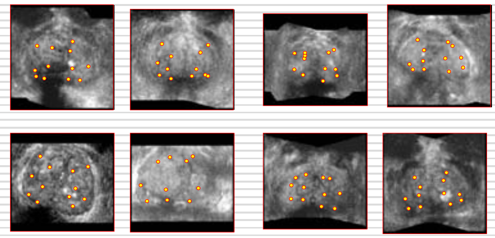
- 3D-representation using 12 sectors



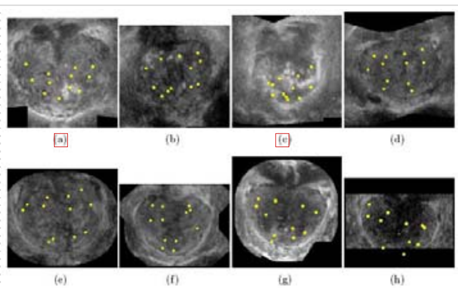
Accuracy evaluation



- 8 patients / 1 operator / transverse plane



Some more ex. (several operators)



Another example [Penney04]

- Rigid registration (multi-slices 2D US to 3D MRI) for image-guided liver puncture
- Failure of NMI use on raw images
- Approach: transform the images into probability maps (does a pixel belongs to the hepatic tree?)
- Register the probability maps using the normalized correlation coefficient

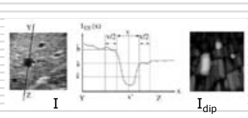
[Penney04]

Example 3 (cont'ed)

- For the MRI: construction of a probability distribution function from manually segmented data

$$p_{MR}(i) = \frac{card\{x \text{ t.q. } x \in vessel \cap MR(x) = i\}}{card\{x \text{ t.q. } x \in liver \cap MR(x) = i\}}$$

- For the US data:
  - Preprocessing: gaussian filtering and artefact removal
  - Looking for « black » regions of width ±v/2 (image I_{dip}) in the direction of the US beam propagation

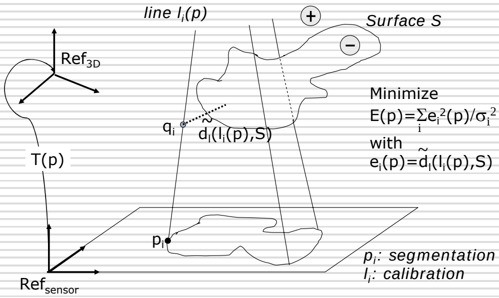


- Construction of the maps and registration

Example 3 (cont'ed)

- Comparison with standard ICP on the segmented data
- rms(TRE)=3.6mm (NMI: 24.8mm)
- Intermediate solution in between « feature-based » and « intensity-based »

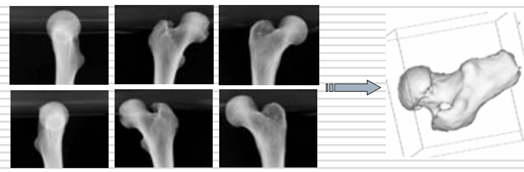
Rigid registration 3D/2D [Lavallée]



Efficient computation of $\tilde{d}_i(l_i(p),S)$ using an octree coding d

Elastic 3D/2D registration using a statistical atlas [Fleute]

- Objective: 3D reconstruction of a given object (ex: femoral bone) using few projections and a priori information



Statistical model

- N instances $m=(x_1,y_1,z_1,\dots,x_n,y_n,z_n)$
- Mean shape:

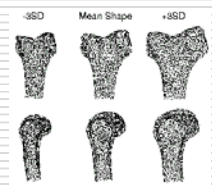
$$\overline{m}=\frac{1}{N}\sum_{i=1}^{N}m_i$$

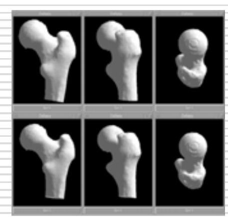
- One instance can be written:

$$m=\overline{m}+\sum_{i=1}^{t}w_i e_i$$

t principal modes
e_i eigenvectors

Example: Deformation modes computed from 16 instances





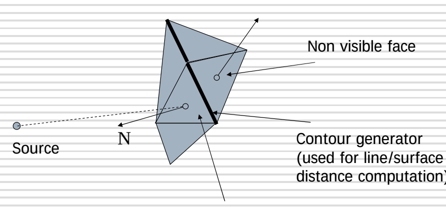
Method

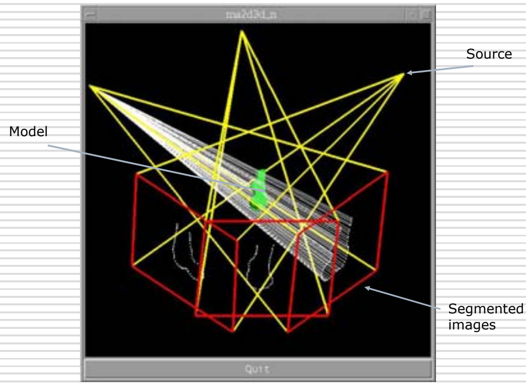
- Computation of the mean shape
- Segmentation of X-ray images and retroprojection line computation
- 3D/2D rigid registration of the mean shape to the projections using ICP
- Optimization of the w_i
  - Looking for the closest point p_j
  - on l_j using « contours generators
  - Simplex algorithm

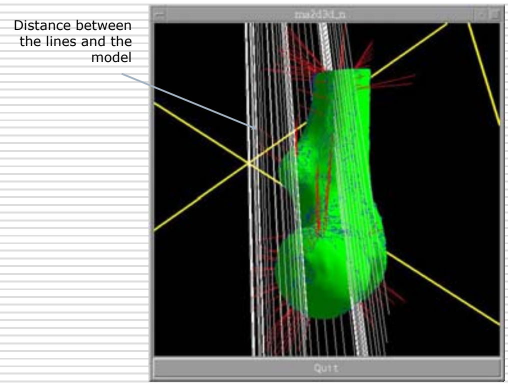
$$E(R,T,w_1,\dots,w_t)=\sum_{j=1}^{p}\min\left\|p_j-(Rg_k(w_1,\dots,w_t)+T)\right\|^2$$

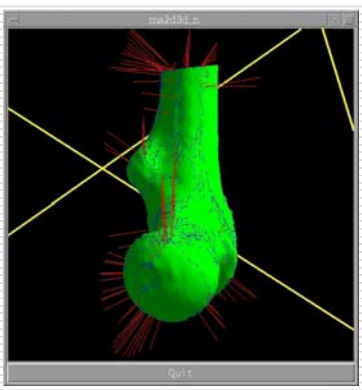
Contour generators

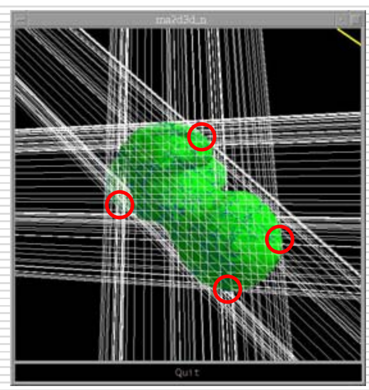
- On a triangular mesh

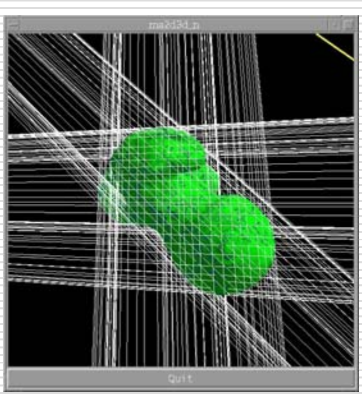












Registration issues

- Optimization pbs (local methods > local minima)
- Evaluation of results
  - General evaluation of an approach
  - « On-line » evaluation during an application

Registration issues: evaluation

- Simulation with synthetic data and/or with known transforms
- Comparison to a « gold standard »
  - Ex: surface registration compared to fiducial registration TRE(a)=$|T(a)-T_g(a)|$
- Evaluation for specific relevant clinical targets (Target Registration Error: TRE = $|T_A^B(a_i)-b_i|$)

$$rms = \sqrt{\sum_{i=1}^{N} \frac{\left|T_A^B(a_i)-b_i\right|^2}{N}}$$

- Consistency analysis
  - 3 non correlated registrations A-B, B-C et C-A (often wrong > under-estimate of the error)

Conclusion

- A very large amount of research work in and out of the medical field
- Theoretical background and well-known classes of methods
- Open issues
  - Elastic registration
  - Evaluation
  - Real-time
  - Etc.