Image Registration and Fusion

Professor Michael Brady FRS FREng
Department of Engineering Science
Oxford University
Image registration & information fusion

• Image Registration:
  – *Geometric* (and *Photometric*) alignment of one image with another
  – Images may be of same or different types (MR, CT, …)

• Information Fusion:
  – No single image modality provides a complete picture in all cases
  – images of different modalities & infer a more comprehensive story than provided by either
Examples of image registration 1
images of a single individual

• Aligning an image taken prior to an operation, to help plan the procedure, with one taken during the operation (for example to avoid use of a stereotactic frame)

• Aligning an image taken now with one taken on a previous occasion (monitor the progression of disease, discover the fact of a disease)

• Aligning images of two objects that are expected, a priori to be "almost" the same

• Aligning two images of different sorts of the same patient (data fusion)
Two brain MRI images of the same patient (3 orthogonal views).

One of the images is taken prior to the operation, in order to plan it; the second while the patient is having the operation: the 6 white dots are the stereotactic frame screwed into the patient’s skull.

In this case, a rigid transform suffices
This shows the situation after the pre-op and inter-op images have been aligned.

Typically, a rigid registration algorithm applied to brain images will be accurate to 1/10 of a voxel and 0.1 degrees of rotation.
MRI-CT image fusion

MRI image volume: soft tissue – show presence of a tumour

Computed tomography (CT), shows bony structures – very accurate
Fusing the two volumes, to find the most probable image transformation is the core of automated radiation therapy planning.
Example: rigid CT/MR registration
Multiple Fusion Algorithms

- **Rigid fusion** – no compensation for motion or patient position

- **Deformable fusion** – crucial when structures have changed position or shape between or during scans due to voluntary or physiological motion or imperfect scanning protocols

Rigid fusion (fig 1) can be ambiguous - the active growth identified on PET might be either one of two CT lesions. However, deformable fusion (fig 2) identifies the PET activity with the anterior lesion on CT.

Example courtesy of Mirada Solutions Ltd software Reveal MVS supplied to Oxford projects
Fusion of information = registration plus combination in a single representation: PET/CT

Example courtesy of Mirada Solutions Ltd software Reveal MVS supplied to Oxford projects
Many Clinical Applications of Fusion

- Cancer staging
- Biopsy planning
- Radiotherapy treatment planning
- Quantitative assessment of treatment response
- Pre-surgical assessment of other conditions e.g. epilepsy
- As an effective communication tool when reporting to clinical meetings, referring physicians or to patients
- Whenever multiple data sources may be better assessed together

*PET data identifies a region of hypometabolism due to epilepsy. Fusion with MR localises the damage to the anterior and medial areas of the right temporal gyrus*

Example courtesy of Mirada Solutions Ltd software Reveal MVS supplied to Oxford projects
Examples of image registration 2
images of a single individual

- Aligning the images from two different patients;
- Aligning the images of a subject to an atlas, or, constructing such an atlas from the images of several subjects;
- Aligning the images of patients and aligning those of normals to develop a statistical model of variation associated with a disease;
- Aligning the images from many thousands of subjects around the world as part of a clinical/drug trial
Two images defined over domains of Euclidean space

T is a transform between the two spaces

T is restricted to the volumes

Then further to the part of a grid inside the volumes

The grid on the overlap has to be resampled

The transformed grids don’t overlap: interpolation is necessary
CT – PET registration

Non-rigid registration is necessary
Rigid registration poor

Is the tumour in the lungs or the stomach?
Non-rigid registration

Looks plausible; but how could you be sure?

Are you prepared to risk your software against getting sued?
Components of registration

Generally, $T(i_k)$ won't lie on a pixel location in $J$, so interpolate:

$I(x_k)$ maps to $J(T(x_k))$

(The down arrow indicates interpolation)

The registration problem can be formulated as:

$$T = \arg \min \sum_k \text{sim}(I(x_k), J(T(x_k)))$$

• What entities do we match? Features, intensities, …
• What interpolation method to use? Bilinear, spline, …
• What class of transforms? Rigid, affine, spline warps, … ✓
• What similarity criterion to use? SSD, … ✓
• What search algorithm to find the minimum $T$?
Simplest similarity criterion: conservation of intensity

\[ \sum_{i,j} p_{i,j} (i - j)^2 \]

This works well in the simplest case; but it is relatively ineffective, even if there is a functional dependence between intensities: as there often is in medical images of different types:

Same anatomy but left is T\(_1\) weighted, right is T\(_2\) weighted
We met the concept of histogram in the segmentation lecture, for example for the pixels in image $I$. Suppose that image $I$ has $N$ pixels, then the histogram is the (discrete approximation to the) probability that a pixel has intensity $i$:

$$p_i = \frac{1}{N} \left| \{ k : I(x_k) = i \} \right|$$
Given a transform $T$, the concept is extended to that of *joint histogram*, the probability that, under $T$, intensity $i$ is paired with $j$:

$$p_{i,j}(T) = \left| \{ k : I(x_k) = i \text{ and } J(T(x_k)) \leq j \} \right|$$

Note that the huge peak in the CT histogram corresponds to the intensity range spanning WM, GM, CSF, since these cannot be distinguished on the basis of x-ray attenuation.
Heuristic observation is that when the images are aligned, the joint histogram appears “sharpest”: “Woods’ criterion”.

Why this should be the case is still not certain!
Heuristic observation is that when the images are aligned, the joint histogram appears “sharpest”
Registration based on Woods’ criterion

Recall the registration problem: find $T = \arg \min \sum_k \text{sim}(I(x_k), J(T(x_k)))$

How?

Initialise $T$ … perhaps mobilising application-specific knowledge

How?

Compute the joint histogram of $I$ and $J(T)$

How?

Is this the sharpest? Are the images as aligned with the current $T$ most similar?

How?

Modify $T$ a bit, in a way that seems likely to increase the sharpness of the joint histogram: $T \leftarrow T + \delta T$

Done! (you hope)

Likely to be a local minimum unless you start near enough the answer!
Statistical similarity

- The hypothesis of a functional dependence, even if it is quite general, remains eminently debatable (and is debated). The classic counter-example is in MRI: the intensities in T1 and T2 images are quite different. Similarly, the intensities from an MRI and from a CT image are entirely different.

- The Joint Histogram becomes a measure of the degree of statistical dependence between the intensities in the two images. From the standpoint of information theory, the most natural measures are based on entropy.
  - This is intuitive, since entropy measures “spread” in a histogram

- The most important refinement is mutual information
Mutual Information

\[ MI(I, J \mid T) = \sum_{i,j} p_{i,j} \log \frac{p_{i,j}}{p_i p_j} \]

Algorithms for maximising mutual information (between intensities) have been the most popular for medical image registration to date.

There are many refinements underway … not least using measurements of local phase instead of intensity*

*Mellor and Brady, Medical Image Analysis, 2004
Registration by maximising mutual information

Derek Hill et. al., Physics in Medicine and Biology, 46, 2001
A different approach: the “Demons” algorithm

Transformation: \( x \rightarrow T(x) = x + v(x) \)

Voxel displacements in gradient direction: \( \nabla (I \circ T_n)(x) \)

Displacements proportional to: \( \| (I \circ T_n)(x) - J(x) \| \)

Smooth with a Gaussian to help numerical stability

\[
v_{n+1}(x) = G_\sigma \otimes \left( v_n(x) + \frac{(I \circ T_n)(x) - J(x)}{\| \nabla (I \circ T_n)(x) \|^2 + \| (I \circ T_n)(x) - J(x) \|^2} \nabla (I \circ T_n)(x) \right)
\]
Non-rigid registration: Mellor, 2004

Two portraits of Henry 8

Registration of (a) into (b)

Left – initial situation
Right – final situation
Simultaneous Segmentation and Registration

- Segmentation can aid registration
- Registration can aid segmentation
- Interleaving segmentation and registration

Given observed images $I$ and $J$, independently degraded by noise but related through some unknown geometric transformation $T$, simultaneously estimate the segmentation label field $f$ and recover the geometric transformation $T$

Chen Xiao Hua and Mike Brady have developed a model for simultaneous registration and segmentation based on the MRF model we studied for segmentation

- Zhang Yong Yue, Smith & Brady (IEEE TMI) for Image Segmentation & Partial Volume Effect
- J.-L. Marroquin, IEEE Trans PAMI, 2002
Two brain images separated by a rigid transformation

Experiment
Simultaneous segmentation and registration
Separate segmentation of left and right images

Simultaneous segmentation & estimation of transformation
Two brain images separated by an affine transformation

Experiment
Simultaneous segmentation and registration
Separate segmentation of left and right images

Simultaneous segmentation & estimation of affine transformation