Image registration and fusion. Problems and feasibility

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Multimodality Imaging for Radiotherapy: state of the art, needs and perspectives
Fusion and registration

Registration: where are we?

Registration: where are we going?
  Robustness: how to deal with errors or differences between the images?
  Transformations: how to deal with non-linear (more than affine) transformations?
  Segmentation through Registration: e.g. Atlas-based segmentation

Conclusion
Fusion versus Registration

Can we fuse information from both modalities?

No, because of the different geometries (no point to point correspondences)
Fusion *versus* Registration

Can we *fuse* information from both modalities? **Yes,** because geometries are the same (point to point correspondences)
Fusion versus Registration

- Fusion: consists in putting together information coming from different sources/data
- Registration: consists in computing the geometrical transformation between two data sets
  - This transformation is used to resample one data set
- A (good) registration is mandatory for a (good) fusion
Registration purpose

• The purpose of registration is to compute the transformation that allows to superimpose two images

• Two questions:
  ▪ What kind of transformation (rigid, …, non-linear)?
  ▪ How to measure quantitatively the quality of a registration?
    – Required to compare transformations

• One (user) requirement:
  ▪ Compute this transformation as fast as possible
Intuitive Example

• How to register these 2 images?
Most simple approach

- The user specifies and pairs points

\[
y_k \quad \quad \quad \quad x_k
\]
Most simple approach

- The search transformed minimises the residuals
  - In mathematical language \( \hat{T} = \arg\min_{T \in T} \sum \| T(x_k) - y_k \|^2 \)
  - Known solutions for most transformations: rigid, affine, …

- Requires user interaction, limited precision
Most simple approach

- One of the image is resampled by $\hat{T}$
- Fusion is then possible
Fusion versus Registration

- FUSION:
  - How to combine information?

Example: add transparency
Fusion and registration

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Conclusion
Multimodal registration: where are we?

- Depends on anatomical localisation
- Cerebral (head) images of same subject: problem solved
- Lot of methods

Segmentation

Landmarks specified and paired by an user

Chamfer matching

No segmentation

Mutual information
Multimodal registration: where are we?

- Depends on anatomical localisation
- Cerebral (head) images: problem solved
- Lot of methods

Distance-based measures  Landmarks specified and paired by an user
Intensity-based measures  Chamfer matching

- Allowed transformations: try to recover a global motion
  - Rigid (no deformations)
  - Affine (allows shearing, and stretching along each direction)
CT/IRM Fusion on Head
CT/PET Fusion on Head
Multimodal registration: where are we?

• Others localisations?
  ▪ Head and Neck:
    – Rigid / Affine may be sufficient if no neck flexion
  ▪ Lungs
    – Rigid / Affine may be sufficient if same respiratory phase
  ▪ Pelvis area
    – Rigid / Affine may be sufficient if no patient movement

• Coupled imaging devices (eg PET/CT) meet partially some of these requirements
  ▪ Patient is asked not to move
  ▪ But can not handle respiratory artefacts (lungs images)
CT/PET Fusion on Lungs
CT/MRI: Fusion on Pelvis (supine/supine)
Fusion and registration

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Multimodal registration: where are we going?

• Extraction of regions of possible errors before registration
  ▪ E.g. tumour segmentation

• Design of robust methods:
  1. Recognize local registration errors
  2. Reject errors

• Example: block matching
“Block Matching”: automated and robust

1. Consider regularly sampled sub-images (or “blocks”)
“Block Matching”: automated and robust

2. Search the “most similar” block: gives point to point correspondence
“Block Matching”: automated and robust

3. Compute transformation

\[ \hat{T} = \arg\min_{T \in \Gamma} \sum \| T(x_k) - y_k \|^2 \]
“Block Matching”: automated and robust

3. Compute transformation
   
   Suppress outliers

\begin{align*}
\hat{T} &= \arg\min_{T \in \Gamma} \sum_{k \in \Gamma} \|T(x_k) - y_k\|^2 \\
\|\hat{T}(x_k) - y_k\|^2 &\geq \rho
\end{align*}

Robustness
“Block Matching”: automated and robust

3. Compute transformation
   \( \hat{T} = \arg\min_{T \in \Gamma} \sum_{k} \|T(x_k) - y_k\|^2 \)
   \( \|\hat{T}(x_k) - y_k\|^2 \geq \rho \)

Robustness
"Block Matching": automated and robust

Global overview

1. Consider regularly sampled sub-images (or “blocks”)
2. Search the “most similar” block: gives point to point correspondence
3. Compute transformation
   
   \[ \hat{T} = \arg \min_{T \in T} \sum_{k} \| T(x_k) - y_k \|^2 \]
   
   \[ \| \hat{T}(x_k) - y_k \| \geq \rho \]

4. Resample image

Iterate until stability
CT/MRI: Fusion on Pelvis (supine/prone)

Mutual information (global) methods fail
Multimodal registration: where are we going?

Use of non-linear (more than affine) transformations
- Try to recover patient’s global and/or local deformations
- Statistics over groups

• Measure of quality made of two terms
  - Quality of registration
  - Quality of the transformation itself. Transformations may deform “too much”: they are constrained by a regularisation term.

• Lot of methods in the literature. They depend on
  - The quality measure of the registration
    - E.g., mutual information
  - The parameterization of the transformations
    - E.g., Splines, Radial Basis Functions, Vector field
  - The regularisation term
    - E.g., elastic when the regularisation is inspired by linear elasticity.
  - No standardized method has not emerged yet

• Difficulty of validation
Affine transformation

Correct size and position but high remaining variability in cortex and deep structures

MR T1 Images
256x256x120 voxels
Fluid regularization

Very good image correspondence

But anatomically meaningless deformation

Jacobian \[\frac{1}{50;50}\]
Adaptive non-stationary visco-elastic regularization

Registration in 5 min on 15 PCs

Anatomically more meaningful deformation

Jacobian $[1/5;5]$
Multi-Affine Framework

- **Goal:**
  - Register only specified anatomic areas (regional landmarks)
  - Interpolate the transformation between the areas
Multi-Affine Framework

- **Global transformation:**
  - Weighted combination of affine transformations
  - Each transformation defined on a specific area

- **Alternate optimization:**
  - Local affine transformations estimation
    - Block-Matching or gradient descent on a similarity measure
  - Regularization of the affine components
    - Ensure coherence between the affine components
Results on Head and Neck Images

Reference image

Resampled floating image
Results on Pelvis Images

Reference image

Resampled floating image
Fusion and registration

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Segmentation through Registration: e.g. Atlas-based segmentation

Conclusion
Atlas based segmentation

• Atlas = Segmented sample
  - Image of the same modality than the one to be segmented
  - + contours

• Principle:
  - To deform an atlas (the image) so that it adapts to the image to be segmented
  - The deformed associated contours yield the segmentation

• The transformation must have a sufficient number of degrees of freedom to handle atlas/subject variability
Principle

First alignment (affine)

ATLAS
Principle

Second alignment (non-linear)

ATLAS
How to build Atlases?

- Schematic drawings
- One image delineated by an expert (Brain Atlas)
  - The image has to be representative of the clinical images
  - The chosen image may bias the results
    - Dissymmetry, ...
- Average image build from many delineated samples (Head and Neck Atlas)
  - Head and Neck: 45 delineated CT images
  - 2 mm thickness
  - UCL, Brussels, Belgium (Prof. V. Grégoire)
Brain Atlas

- Atlas = artificial MR image (MNI simulator) + segmentation of structures of interest (P-Y Bondiau, MD, CAL, Nice, France)
Brain Atlas in TPS
Head and Neck Atlas: delineated images
Atlas by averaging

45 patients
Qualitative results

Manual Segmentation
Preliminary results

Atlas based Segmentation
Conclusion

• State of the Art: Automated Multimodal Registration
  ▪ Rigid / Affine Transformation: solved
  ▪ Head localization: +
  ▪ Other localization (pelvis, lungs, head and neck) : +/-

• Developments
  ▪ Robust Methods
    – Allows anatomical differences
  ▪ Non-Linear Transformations
    – Allows deformations
    – Difficult to tune (regularisation, …)

• Applications
  ▪ Statistics on populations
  ▪ Atlas-based segmentation
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