Registration-based approaches in cardiac MR imaging

D. Rueckert, Ph.D.
d.rueckert@imperial.ac.uk
http://www.doc.ic.ac.uk/~dr

Visual Information Processing, Dept. of Computing, Imperial College, London, UK

Overview

• Introduction
• Image registration
• Registration for cardiac segmentation
  – atlas-based segmentation
  – statistical models
  – probabilistic models
• Registration for motion modelling
  – cardiac motion
  – respiratory motion
• Conclusions

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  Cardiovascular MR Imaging
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  Cardiac image-guided interventions

Image Registration

C. Ruff, 1995
Image Registration

• Transformation $T$ which defines the spatial relationship between the two images:
  
  \[ T : (x, y, z) \rightarrow (x', y', z') \]

  where $(x,y,z)$ denotes points in the target image and $(x',y',z')$ denotes the corresponding points in the source image.

• Types of similarity measures (depending on application)
  - Features: points (landmarks), lines or surfaces
  - Intensities

• Types of transformations (depending on application)
  - Rigid or affine transformation
  - Non-rigid transformation

Image to image registration

• Intra-subject registration
  - Aim: the registration of images of the same subject
    - images from different modalities (multi-modal registration)
    - images from same modality (mono-modal registration)
  - Purpose:
    - to combine anatomical and functional information of different imaging modalities (MR + SPECT/PET)
    - to compensate for patient motion but also cardiac or respiratory motion

• Inter-subject registration
  - Aim: the registration of the images of different subjects and/or models.
  - Purpose: compare data in a standardized coordinate system (i.e. with an atlas)

• Serial registration
  - Aim: the registration of a sequence of images (over time) of the same subject.
  - Purpose: to monitor temporal changes
    - within examinations (cardiac motion)
    - between examinations (rest/stress, repeat studies)

Image to physical space registration

• Relating imaging device coordinates to the physical space of the patient

• Applications:
  - planning of procedures (i.e. RF ablations)
  - navigation during interventions

• Registration of:
  - extrinsic markers fixed to the patient at scanning and operation time
  - intrinsic markers (anatomical landmarks, image features)
  - intra-operative images (ultrasound, X-ray or X-ray fluoroscopy) to pre-operative image
Image to physical space registration: Example

- XMR = X-Ray + MR in same room
- Common sliding patient table
- Provides path to MR-guided intervention

XMR system at Guy’s Hospital, London

Image-Guided Cardiac Interventions

- x-ray
- MR rendering
- x-ray + MR rendering

Rhode et al. IEEE TMI 2003

Image Registration

1. Initial transformation $T$
2. Calculate cost function $C$ for transformation $T$
3. Generate new estimate of $T$ by minimizing $C$
4. Update transformation $T$
5. Is new transformation an improvement?
6. Optimization

Rhode et al. IEEE TMI 2003
Registration based on voxel similarity

- Registration based on geometric features is independent of the modalities from which the features have been derived
- Registration based on voxel similarity measures features must make a distinction between
  - monomodality registration:
    • CT-CT, MR-MR, PET-PET, etc
  - multimodality registration
    • MR-CT, MR-PET, CT-PET, etc

Sums of Squared Differences (SSD)

\[ C = \frac{1}{N} \sum_{i} (I_{A}(p_{i}) - I_{B}(T(p_{i})))^2 \]

- assumes an identity relationship between image intensities in both images
- optimal measure if the difference between both images is Gaussian noise
- sensitive to outliers

Normalized Cross Correlation (CC)

\[ C = \frac{\sum (I_{A}(p) - \mu_{A})(I_{B}(T(p)) - \mu_{B})}{\sqrt{\sum (I_{A}(p) - \mu_{A})^2 \sum (I_{B}(T(p)) - \mu_{B})^2}} \]

- \( \mu_{A} \) average intensity in image A
- \( \mu_{B} \) average intensity in image B
- assumes a linear relationship between image intensities
- useful if images have been acquired with different intensity windowing

2D Histograms

D. Hill et al.
2D Histograms

- MR/CT
- MR/PET

Voxel similarity based on information theory

- Mutual Information (Viola et al. and Collignon et al.)
  \[ I(A, B) = H(A) + H(B) - H(A, B) \]
  describes how well one image can be explained by another image but is dependent on the amount of overlap between images.
- Normalized Mutual Information (Studholme et al.)
  \[ I(A, B) = \frac{H(A) + H(B)}{H(A, B)} \]
  can be shown to be independent of the amount of overlap between images.

Transformations

- Types of transformations
  - rigid transformations
  - affine transformations
  - polynomial transformations
    - linear
    - quadratic
    - cubic
  - spline-based transformations
  - elastic transformations
  - fluid transformations
Non-rigid transformations

Before deformation  
After deformation

Displacement in the horizontal direction  
Displacement in the vertical direction

Non-rigid registration using FFDs

- Non-rigid registration is based on a combination of global and local transformations:
  \[ T(x) = T_{\text{global}}(x) + T_{\text{local}}(x) \]

- Local transformation is represented by a free-form deformation (FFD) based on B-splines:
  \[ T_{\text{local}}(x) = \sum_{i,j,k,l=0}^{3} B_i(u)B_j(v)B_k(w)c_{i,j,k,l} \]
  controlled by a mesh of control points \( c \)

- Control point locations are found by maximizing a similarity measure (e.g. mutual information)

source  
Rueckert et al/IEEE TMI 1999

target
Non-rigid registration

• Soft constraints

\[ C = -C_{\text{similarity}} + \lambda C_{\text{smooth}} \]

\[ C_{\text{smooth}} = \sum_{i=1}^{3} \left( \frac{\partial T}{\partial x} \right)^2 + \left( \frac{\partial T}{\partial y} \right)^2 + \left( \frac{\partial T}{\partial z} \right)^2 + 2 \left( \frac{\partial T}{\partial xy} \right)^2 + \left( \frac{\partial T}{\partial xz} \right)^2 + \left( \frac{\partial T}{\partial yz} \right)^2 \]

• Hard constraints
  - volume preservation
  - mass preservation
    S. Haker et al, IJCV, 60(3): 225-240, 2004

\[ \text{det} \left( \begin{array}{ccc} \frac{\partial T}{\partial x} & \frac{\partial T}{\partial y} & \frac{\partial T}{\partial z} \\ \frac{\partial T}{\partial x} & \frac{\partial T}{\partial y} & \frac{\partial T}{\partial z} \\ \frac{\partial T}{\partial x} & \frac{\partial T}{\partial y} & \frac{\partial T}{\partial z} \end{array} \right) = 1 \]

Challenges for cardiac image registration

• Cardiac anatomy has only a few anatomical landmarks
• Cardiac anatomy requires more than 4D modelling
• Cardiac image acquisition
  – data is often highly anisotropic
  – data is often acquired in different breath-holds so 3D data can be inconsistent
  – imaging contrast can be changing (e.g. in tagging)

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Atlas-based segmentation

• Segmentation via registration:
  Apply \( T \) by non-rigid registration
  Propagate segmentation
Atlas-based segmentation

Myocardial Delineation via Registration in a Polar Coordinate System.
N.M.I. Noble et al., MICCAI 2002

Computational modelling of anatomy

- Substantial variability of cardiac anatomy
  - across subjects
  - across cardiac cycle
- How can we model variability?
  - probabilistic models (probabilistic atlases are widely used for other anatomical structures, in particular in the brain)
  - statistical models (active shape models, active appearance models)
- Requires registration of images and models into a common coordinate system

Need for 4D cardiac registration

- The heart is undergoing spatially and temporally a varying degree of motion during the cardiac cycle
- 3D spatial registration of corresponding frames of the image sequences is not sufficient because of
  - differences in the acquisition parameters
  - differences in the length of cardiac cycles
  - differences in the dynamic properties of the hearts
**Need for 4D cardiac registration**

- Which 4D transformation model is appropriate?
  
  a) \( T(x, y, z, t) = (x'(x, y, z, t), y'(x, y, z, t), z'(x, y, z, t), t'(x, y, z, t)) \)
  
  b) \( T(x, y, z, t) = (x'(x, y, z, t'), y'(x, y, z, t'), z'(x, y, z, t'), t'(t)) \)
  
  c) \( T(x, y, z, t) = (x'(x, y, z), y'(x, y, z), z'(x, y, z), t'(t)) \)

  a) doesn’t preserve temporal causality
  
  b) spatial registration is variable in time
  
  c) spatial registration is fixed in time

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**4D cardiac registration**

- Use a decoupled transformation model:
  
  \[ T_{\text{spatial}}(x, y, z) = (x'(x, y, z), y'(x, y, z), z'(x, y, z)) \]
  
  \[ T_{\text{temporal}}(t) = t'(t) \]

  - Both components can be modelled with rigid and non-rigid transformations (i.e. splines)
  
  - Similarity measure (mutual information) can be computed over the region of overlap of two 4D image sequences

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**4D statistical shape models**

- Shape models can be extended to 4D (e.g. for cardiac applications)
  
  - Shape model separates shape variability:
    
    - between subjects (across the population)
    
    - within subjects (during the cardiac cycle)

  - Assumption: \( q_i \) shapes (\( n_p \) subjects and \( n_f \) time frames)
  
  - Traditional shape model:
    
    \[ C_{\text{total}} = \frac{1}{n_f n_p} \sum_{i=1}^{n_p} \sum_{k=1}^{n_f} (q_{ik} - q)(q_{ik} - q)^T \]
4D statistical shape models

- Shape model separates shape variability:

\[
C_{\text{within}} = \frac{1}{n_f n_p} \sum_{i=1}^{n_f} \sum_{j=1}^{n_p} (q_{ij} - \bar{q}_j)(q_{ij} - \bar{q}_j)^T
\]

\[
C_{\text{between}} = \frac{1}{n_p} \sum_{i=1}^{n_p} (\bar{q}_i - \bar{q})(\bar{q}_i - \bar{q})^T
\]

Cross-subject shape variability
Within-subject shape variability

1\textsuperscript{st} mode 2\textsuperscript{nd} mode 3\textsuperscript{rd} mode

Tissue classification

Blood pool
Myocardium
Background

Blood pool
Myocardium
Background (RV & LV)
**Tissue classification using EM-based segmentation**

- Classification:
  \[ p(z_i = j | y_i, \Phi) = \frac{p(y_i | z_i = j, \Phi) p(z_i = j)}{\sum_j p(y_i | z_i = j, \Phi) p(z_i = j)} \]

- Estimation of the parameters:
  \[ \mu_j = \frac{\sum y_i p(z_i = j | y_i, \Phi)}{\sum p(z_i = j | y_i, \Phi)} \]
  \[ \sigma_j^2 = \frac{\sum p(z_i = j | y_i, \Phi)(y_i - \mu_j)^2}{\sum p(z_i = j | y_i, \Phi)} \]

**Cardiac atlas construction**

- Manual segmentations from 14 subjects
- Alignment
- Atlas construction

**4D Probabilistic Atlas: LV, RV, Myocardium**

- LV
- Myocardium
- RV
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**Segmentation algorithm**

- Atlas registration
- Initial parameters \( p, c^2 \)
- First classification EM and atlas
- Classification EM, atlas, MRF, LCC


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**Results from 14 patients**

- LV (mL) vs. time
- Myocardium (mL) vs. time
- RV (mL) vs. time

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**Cardiac motion tracking**

- Right Ventricle
- Left Ventricle
- Myocardium
Cardiac motion tracking

- Technique for placing non-invasive markers (a series of planes) in the heart for motion tracking:
  - Zerhouni et al. 1988 who used parallel saturation planes with a conventional spin-echo sequences
  - Axel and Dougherty 1989 proposed tagging in form of SPAMM (spatial modulation of magnetization)
- Analysis of tagged MR is difficult
  - long-axis and short axis images must be taken to reconstruct complete 4D displacement field
  - tags contrast and persistence limited by T1 relaxation
  - tags are difficult to localize automatically
  - variety of approaches: snakes, optical flow, HARP, Gabor filters

Cardiac motion tracking using registration

- A single free-form deformation is defined on a domain \( \Omega \) by a mesh of control points.
- Registration algorithm aligns simultaneously the short- and long-axis images at time \( t \) to the corresponding images at time \( t \rightarrow 0 \).
- Mutual information is used to measure the degree of registration between images

Cardiac motion tracking

\[
T_{(0,1)}^{(t)}(x) = \sum_{i=1}^{J} D_{(0,1)}^{(t)}(x) + x
\]

Cardiac motion tracking: Using short-axis and long-axis MR images

- Challenges: To estimate a 4D motion model we need to register both short-axis (SA) and long-axis (LA) images simultaneously.
- Similarity measure:

\[ I(A, B) = w_{SA} I_{SA}(A, B) + w_{LA} I_{LA}(A, B) \]

- SA and LA images are registered using information in DICOM header, but differences in breath-hold position can lead to inconsistencies.
- Interpolation is difficult because imaging planes (SA, LA) are not parallel.
Cardiac motion tracking

Results using a cardiac motion simulator

Results using a cardiac motion simulator

Results of in-vivo motion tracking

• 11 normal subjects
  • 2 subjects with short-axis MR images, 9 subjects with short-axis and long-axis MR images acquired on a Siemens Sonata 1.5T
  • Tagged EPI, multi-slice, breath-hold acquisition, acquisition time: 10-15 minutes, 256 x 256 x 10, voxels dimensions: 1.36 x 1.36 x 10mm
• Manual tag tracking used as gold standard
Extraction of contractility parameters

Clinical Case: RF ablation

Comparison with a normal subject under stress

Cartesian vs cylindrical free-form deformations

- Idea: Adapt geometry of FFD to cardiac anatomy
- Goal: Reduce degrees of freedom which need to be optimized during motion tracking
**Cartesian vs cylindrical free-form deformations**

- Ignore control points which cannot influence myocardial motion

**Free-form deformations with lattices of arbitrary topology**

- Based on the idea of subdivision curves (Chaikin's corner cutting algorithm) and surfaces:
  - In the limited approaches cubic B-spline curve or surface

**Free-form deformations with lattices of arbitrary topology**

- Can be extended to surface of arbitrary topology (Catmull & Clark, 1976)
- Extension to volumes of arbitrary topology proposed by MacCracken and Joy in 1996
- An initial base lattice is recursively refined to generate a sequence of lattices which converges to a volume
- Lattices of arbitrary topology can be used

**Example**

- In the limited approaches cubic B-spline curve or surface
Deformation process

- Construct base lattice
- Choose the number of subdivision levels
- Fit lattice to object being deformed
  - i.e. Find which cell each point in the object lies in and the local coordinates of the point within the cell
- Move base lattice vertices and recompute position of points defining object

Lattice construction
Motion tracking using registration

- After lattice is constructed it is “frozen” to the image volume taken at end-diastole, i.e., local cell coordinates of image points within the subdivision volume are computed and cached
- Motion tracking is done by registering the sequence of images taken during systole to the image taken at end-diastole
- Gradient descent optimization procedure using mutual information as image similarity measure
- 80 control points in base lattice (240 degrees of freedom), 3 levels of subdivision
Preliminary results

Comparing cardiac motion from untagged MR vs. tagged MR

Tagged

Untagged
Respiratory motion correction

- Cardiac deformation is caused by two major sources
  - cardiac contraction
  - respiratory motion (breathing)
- Respiratory motion can be prevented by respiratory gating
  - slows down image acquisition
- Respiratory motion correction is required
  - for perfusion studies
  - for high-resolution imaging

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Conclusions

- Registration plays an important role in cardiac image analysis
- Registration in cardiac image analysis
  - Construction of shape models
  - Atlas-based segmentation
- Registration in motion analysis
  - Cardiac motion tracking
  - Cardiac and respiratory motion correction (i.e. perfusion)
- Registration in multi-modal fusion
  - MR/PET/SPECT
  - MR/US
- Registration for image-guided interventions

A study of the motion and deformation of the heart due to respiration
K. McLeish et al., IEEE Transactions on Medical Imaging, Volume 21, Issue 9, Sept. 2002 Page(s):1142 - 1150
Future directions

• Increasing move towards computational anatomy
  – use of standardised coordinate systems and databases
  – models of populations and disease
  – models of the entire cardiovascular system, not only of the LV (and RV), including DT-MRI information
  – registration plays key role for normalisation and comparison of anatomy
• Increasing use of motion models for intelligent image acquisition
  – patient-specific models of cardiac and respiratory motion (e.g. for coronary MRI)
  – motion prediction