Registration-based approaches in cardiac MR imaging

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  Cardiovascular MR Imaging
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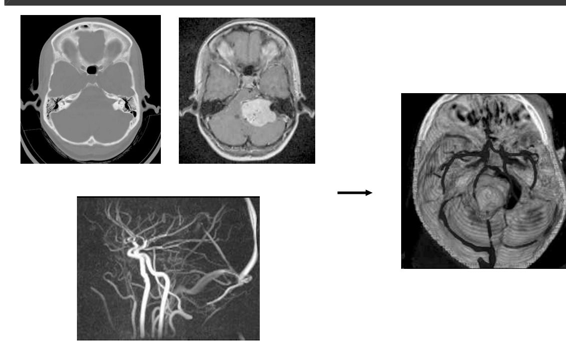
Overview

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

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

Image to image registration

- 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

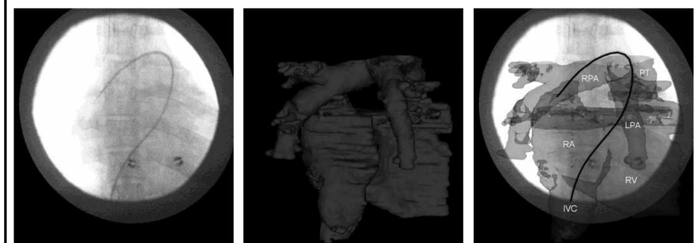
- Relating imaging device coordinates to the physical space of the patient
- Applications:
  - planning of procedures (i.e. RF ablations)
  - navigation during interventions
- Registration of:
  - *extrinsic* markers fixed to the patient at scanning and operation time
  - *intrinsic* markers (anatomical 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

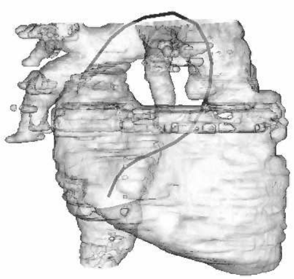
Image-Guided Cardiac Interventions



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

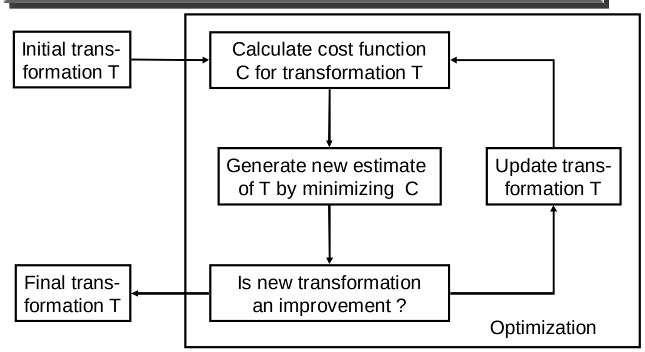
Rhode et al.
IEEE TMI 2003

Image-Guided Cardiac Interventions



Rhode et al.
IEEE TMI 2003

Image Registration



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

Registration based on voxel similarity

- Sums of Squared Differences (SSD)

$$C = \frac{1}{N}\sum_i (I_A(\mathbf{p}_i) - I_B(\mathbf{T}(\mathbf{p}_i)))^2$$

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

Mono-modal image registration

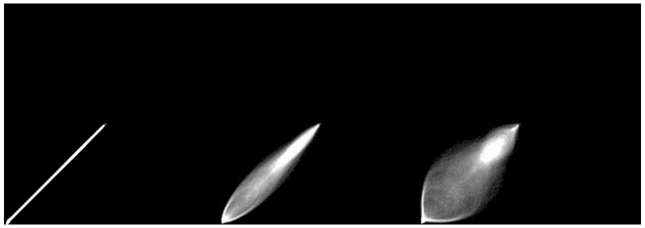
- Normalized Cross Correlation (CC)

$$C = \frac{\sum (I_A(\mathbf{p}) - \mu_A)(I_B(\mathbf{T}(\mathbf{p})) - \mu_B)}{\sqrt{\left(\sum (I_A(\mathbf{p}) - \mu_A)^2\right)\left(\sum (I_B(\mathbf{T}(\mathbf{p})) - \mu_B)^2\right)}}$$

  - μ_A average intensity in image A
  - μ_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

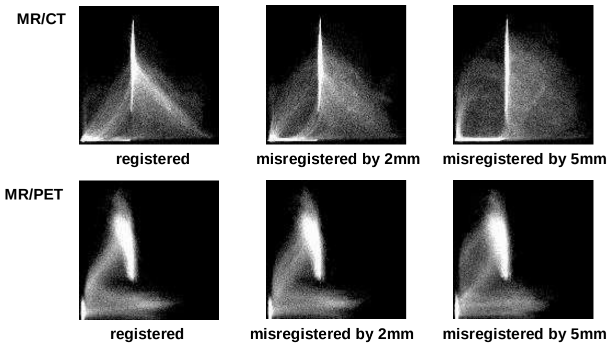
MR/MR



registered misregistered by 2mm misregistered by 5mm

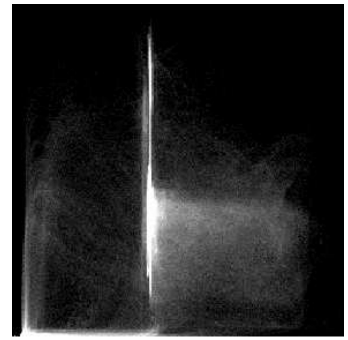
D. Hill et al.

2D Histograms



D. Hill et al.

2D Histograms



D. Hill et al.

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.)

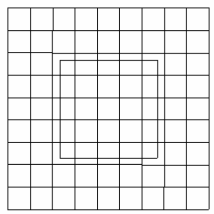
$$I(A,B) = \frac{H(A) + H(B)}{H(A,B)}$$

can be shown to be independent of the amount of overlap between images.

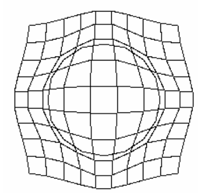
Transformations

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

Non-rigid transformations

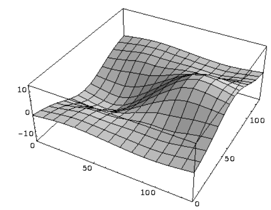


Before deformation

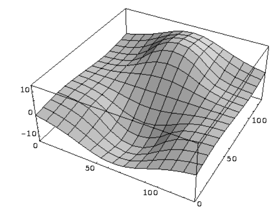


After deformation

Non-rigid transformations



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:

$$\mathbf{T}(\mathbf{x}) = \mathbf{T}_{global}(\mathbf{x}) + \mathbf{T}_{local}(\mathbf{x})$$

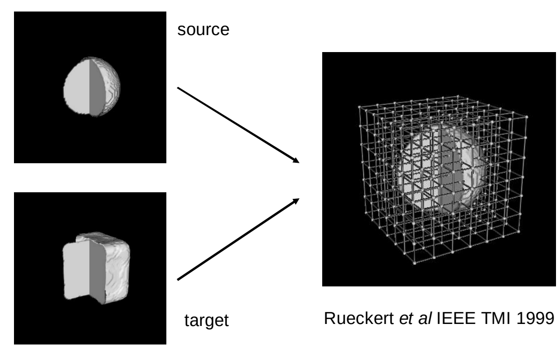
- Local transformation is represented by a free-form deformation (FFD) based on B-splines:

$$\mathbf{T}_{local}(\mathbf{x}) = \sum_{l=0}^{3}\sum_{m=0}^{3}\sum_{n=0}^{3} B_l(u)B_m(v)B_n(w)\mathbf{c}_{i+l,\,j+m,k+n}$$

controlled by a mesh of control points $\mathbf{c}$

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

Non-rigid registration using FFDs



Rueckert *et al* IEEE TMI 1999

Non-rigid registration

- Soft constraints

$$C = -C_{similarity} + \lambda C_{smooth}$$

$$C_{smooth} = \iiint \left(\frac{\partial^2 T}{\partial x^2}\right)^2 + \left(\frac{\partial^2 T}{\partial y^2}\right)^2 + \left(\frac{\partial^2 T}{\partial z^2}\right)^2 + 2\left[\left(\frac{\partial^2 T}{\partial xy}\right)^2 + \left(\frac{\partial^2 T}{\partial xz}\right)^2 + \left(\frac{\partial^2 T}{\partial yz}\right)^2\right]$$

- Hard constraints
  - volume preservation

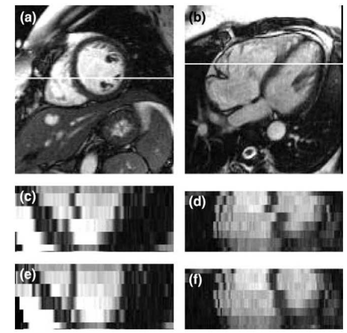
    E. Haber and J. Modersitzki, Inverse Problems 20:1621-1638, 2004.
  - mass preservation

    S. Haker et al, IJCV, 60(3): 225-240, 2004

$$\det\begin{pmatrix} \frac{\partial T_x}{\partial x} & \frac{\partial T_x}{\partial y} & \frac{\partial T_x}{\partial z} \\ \frac{\partial T_y}{\partial x} & \frac{\partial T_y}{\partial y} & \frac{\partial T_y}{\partial z} \\ \frac{\partial T_z}{\partial x} & \frac{\partial T_z}{\partial y} & \frac{\partial T_z}{\partial z} \end{pmatrix} = 1$$

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)



J. Lötjönen et al., Medical Image Analysis, 8(3) , September 2004, Pages 371-386

Overview

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- Registration for cardiac segmentation
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  - statistical models
  - probabilistic models
- Registration for motion modelling
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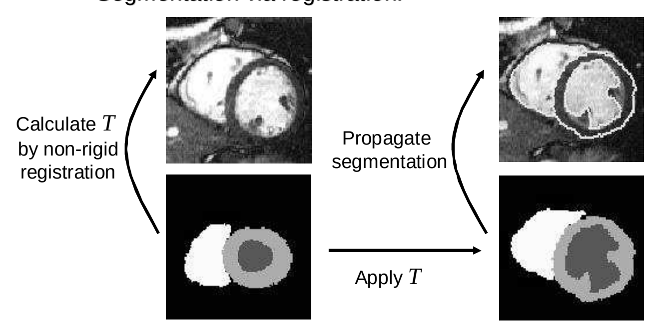
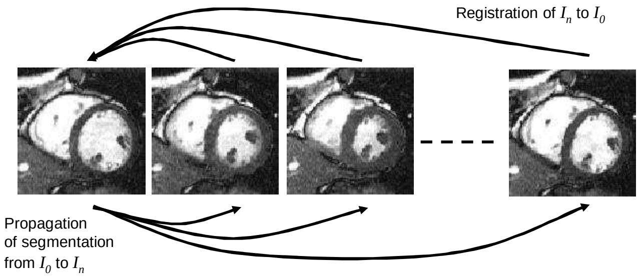
  - respiratory motion
- Conclusions

Atlas-based segmentation

- Segmentation via registration:

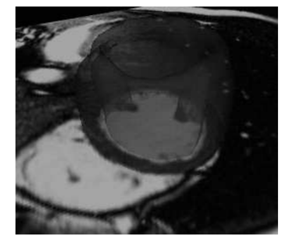


Atlas-based segmentation



Myocardial Delineation via Registration in a Polar Coordinate System. N.M.I.Noble et al., MICCAI 2002
Atlas-based segmentation and tracking of 3D cardiac MR images using non-rigid registration. M. Lorenzo-Valdes et al., MICCAI 2002

Atlas-based segmentation



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) $\mathbf{T}(x,y,z,t) = (x'(x,y,z,t), y'(x,y,z,t), z'(x,y,z,t), t'(x,y,z,t))$

b) $\mathbf{T}(x,y,z,t) = (x'(x,y,z,t'), y'(x,y,z,t'), z'(x,y,z,t'), t'(t))$

c) $\mathbf{T}(x,y,z,t) = (x'(x,y,z), y'(x,y,z), z'(x,y,z), t'(t))$

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

4D cardiac registration

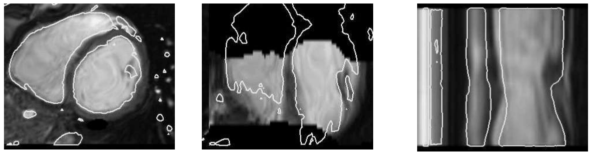
- Use a decoupled transformation model:

$$\mathbf{T}_{spatial}(x,y,z) = (x'(x,y,z), y'(x,y,z), z'(x,y,z))$$

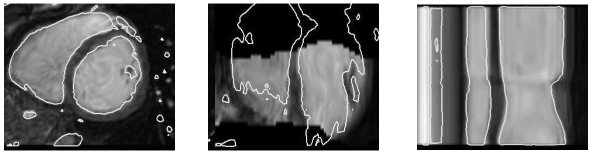
$$\mathbf{T}_{temporal}(t) = t'(t)$$

- 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

4D cardiac registration



3D non-rigid registration



4D non-rigid registration

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_{ik} shapes (n_p subjects and n_f time frames)
- Traditional shape model:

$$\mathbf{C}_{total} = \frac{1}{n_f n_p} \sum_{i=1}^{n_p} \sum_{k=1}^{n_f} (\mathbf{q_{ik}} - \bar{\mathbf{q}})(\mathbf{q_{ik}} - \bar{\mathbf{q}})^T$$

4D statistical shape models

- Shape model separates shape variability:

$$\mathbf{C}_{within} = \frac{1}{n_f n_p} \sum_{i=1}^{n_p} \sum_{k=1}^{n_f} (\mathbf{q}_{\mathbf{ik}} - \bar{\mathbf{q}}_{\mathbf{i}})(\mathbf{q}_{\mathbf{ik}} - \bar{\mathbf{q}}_{\mathbf{i}})^T$$

$$\mathbf{C}_{between} = \frac{1}{n_p} \sum_{i=1}^{n_p} (\bar{\mathbf{q}}_{\mathbf{i}} - \bar{\mathbf{q}})(\bar{\mathbf{q}}_{\mathbf{i}} - \bar{\mathbf{q}})^T$$

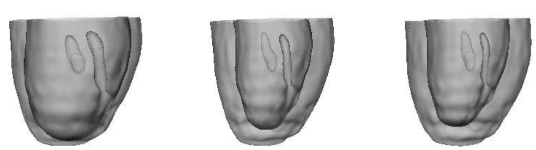
Cross-subject shape variability

Within-subject shape variability

1st mode **2nd mode** **3rd mode**

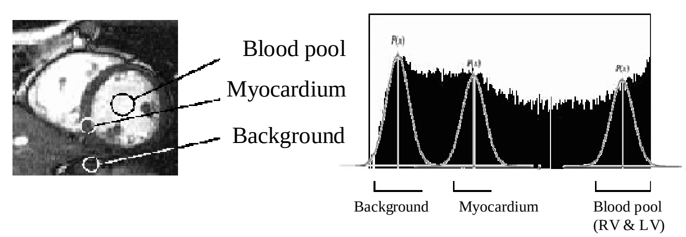
Cross-subject shape variability

Within-subject shape variability



1st mode **2nd mode** **3rd mode**

Tissue classification



Tissue classification using EM-based segmentation

- Classification:

$$p(z_i = j \mid y_i, \Phi) = \frac{p(y_i \mid z_i = j, \Phi_j)\, p(z_i = j)}{\sum_j p(y_i \mid z_i = j, \Phi_j)\, p(z_i = j)}$$

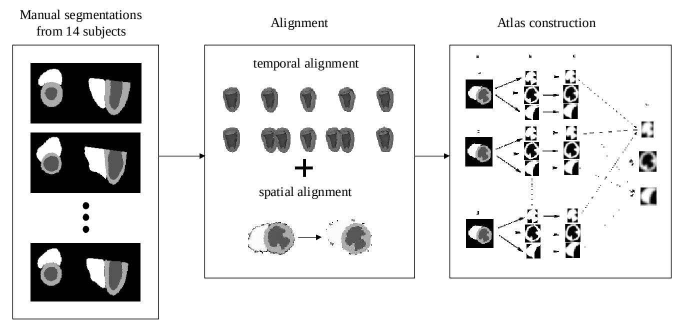
- Estimation of the parameters:

$$\mu_j = \frac{\sum_i y_i\, p(z_i = j \mid y_i, \Phi)}{\sum_i p(z_i = j \mid y_i, \Phi)}$$

$$\sigma_j^2 = \frac{\sum_i p(z_i = j \mid y_i, \Phi)(y_i - \mu_j)^2}{\sum_i p(z_i = j \mid y_i, \Phi)}$$

j = tissue classes

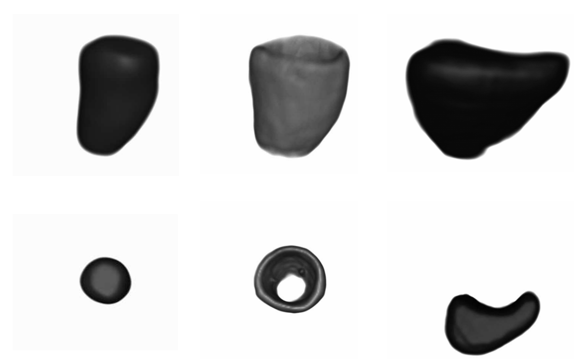
Cardiac atlas construction



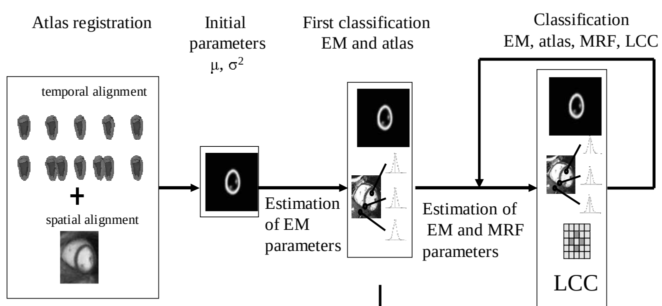
4D Probabilistic Atlas: LV, RV, Myocardium

LV Myocardium RV

4D Probabilistic Atlas: LV, RV, Myocardium

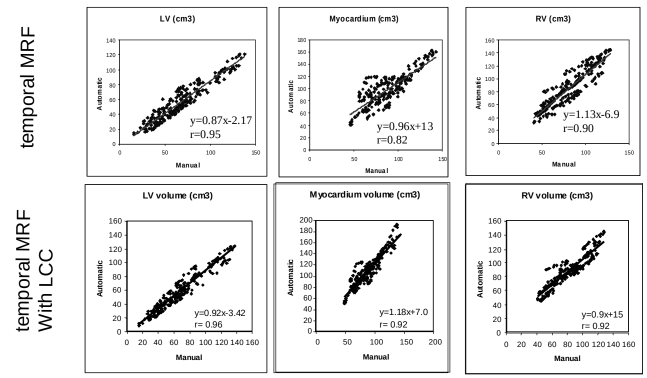


Segmentation algorithm



M. Lorenzo-Valdes et al. Segmentation of 4D cardiac MR images using a probabilistic atlas and the EM algorithm. Medical Image Analysis, 8(3):255-265, 2004.

Results from 14 patients



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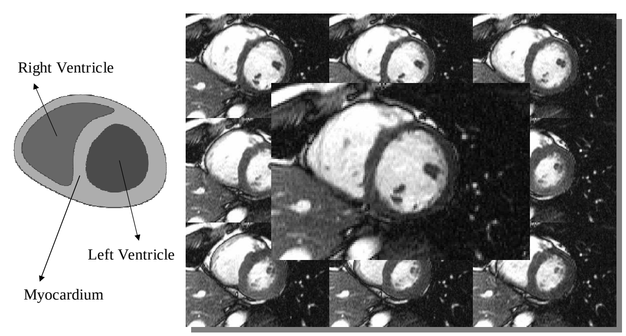
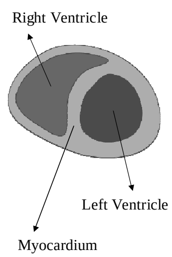
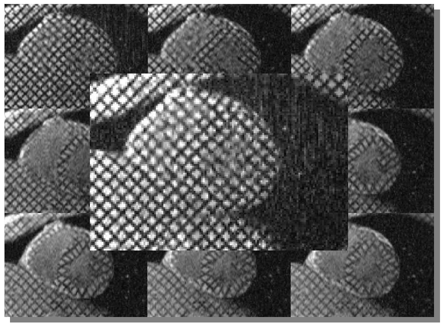
Cardiac motion tracking



Cardiac motion tracking



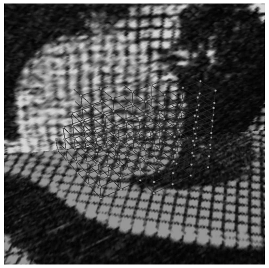


Cardiac motion tracking

- 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

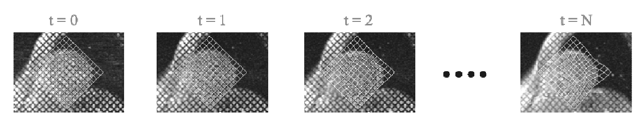
Cardiac motion tracking using registration

- A single free-form deformation is defined on a domain Ω 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 = 0*.
- Mutual information is used to measure the degree of registration between images



R. Chandrashekara et al. IEEE Transactions on Medical Imaging, 23(10):1245–1250, 2004.

Cardiac motion tracking



$$\mathbf{T}^{S}_{(0,1)}(\mathbf{x})$$

$$\mathbf{T}^{S}_{(0,2)}(\mathbf{x})$$

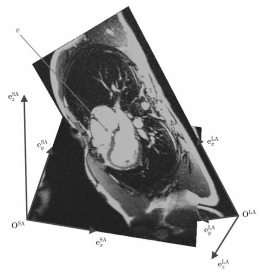
$$\mathbf{T}^{S}_{(0,t)}(\mathbf{x}) = \sum_{i=0}^{T-1} \mathbf{D}^{S}_{(i,i+1)}(\mathbf{x}) + \mathbf{x}$$

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

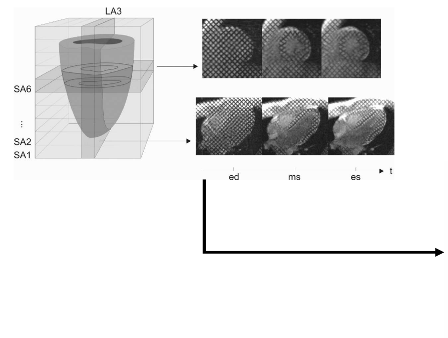
- Challenges: To estimate a 4D motion model we need to register both short-axis (SA) and long-axis (LA) images simultaneously
- Similarity measure:

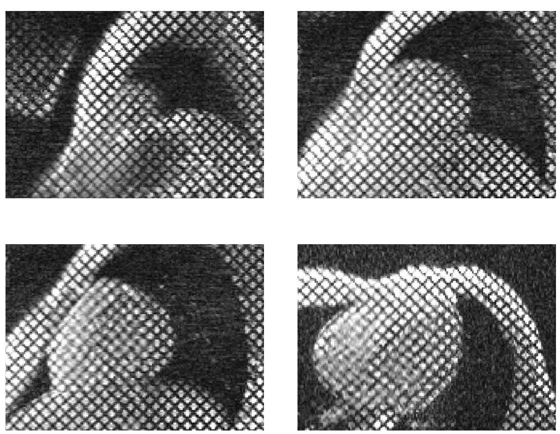
$$I(A,B) = w_{SA} I_{SA}(A,B) + w_{LA} I_{LA}(A,B)$$

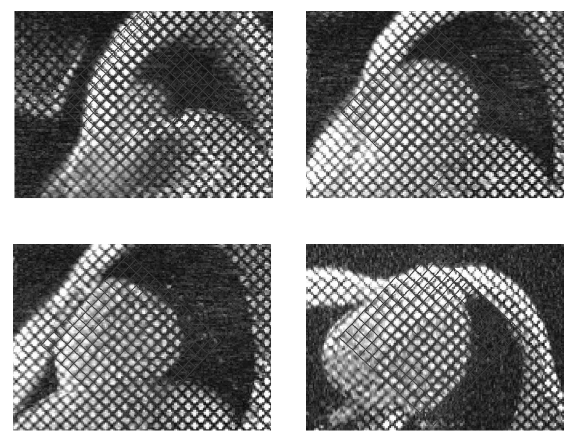
- SA and LA images are registered using information in DICOM header, but differences in breath-hold position can lead to inconsistencies
- Interpolation is difficult because imaging planes (SA, LA) are not parallel



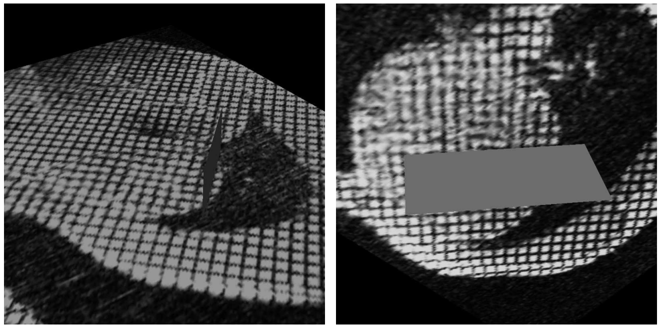
Cardiac motion tracking: Using short-axis and long-axis MR images



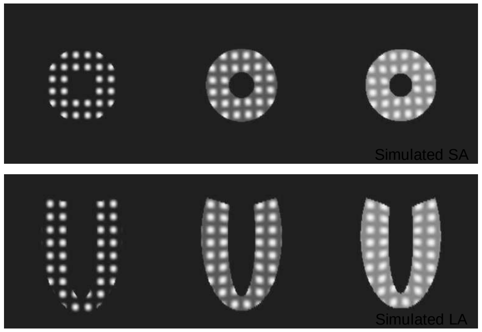




Cardiac motion tracking



Results using a cardiac motion simulator



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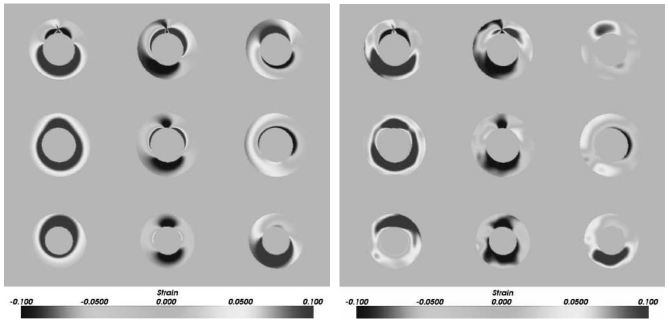
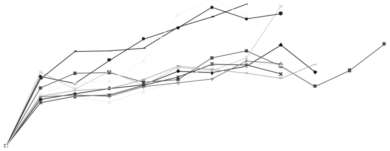
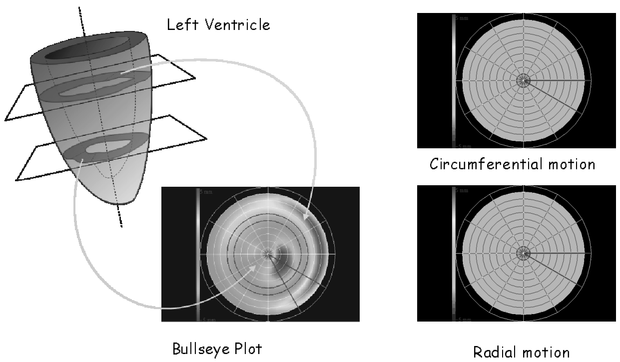


Results of in-vivo motion tracking

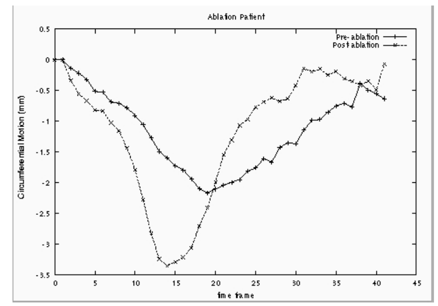
- 11 normal subjects
  - 2 subjects with short-axis MR images, 9 subjects with short-axis and long axis MR images acquired on a Siemens Sonata 1.5T
  - tagged EPI, multi-slice, breath-hold acquisition, acquisition time: 10-15 minutes, 256 x 256 x 10, voxels dimensions: 1.36 x 1.36 x 10mm
- Manual tag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



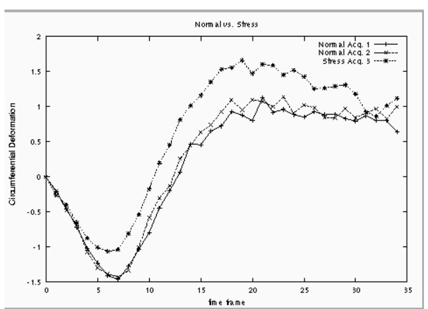
Extraction of contractility parameters



Clinical Case: RF ablation

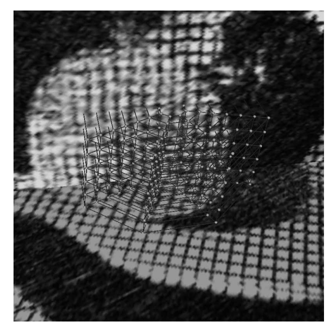


Comparison with a normal subject under stress



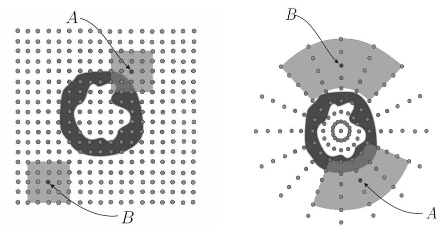
Cartesian vs cylindrical free-form deformations

- Idea: Adapt geometry of FFD to cardiac anatomy
- Goal: Reduce degrees of freedom which need to be optimized during motion tracking



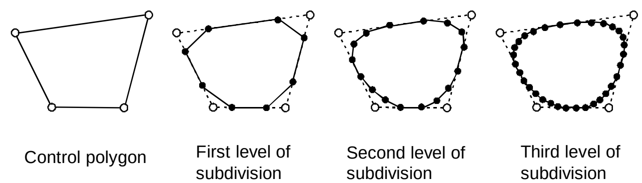
Cartesian vs cylindrical free-form deformations

- 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:

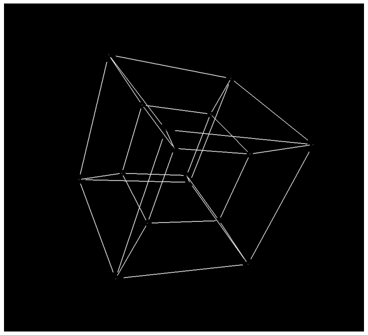


- In the limited approaches cubic B-spline curve or surface

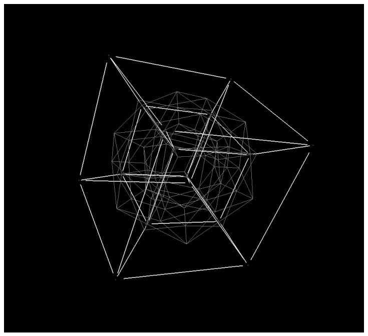
Free-form deformations with lattices of arbitrary topology

- 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

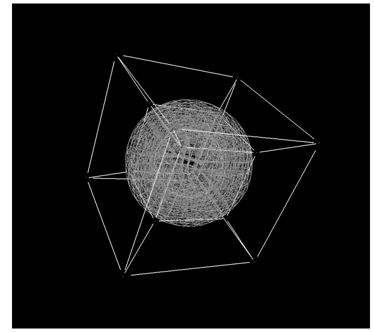
Example



Example



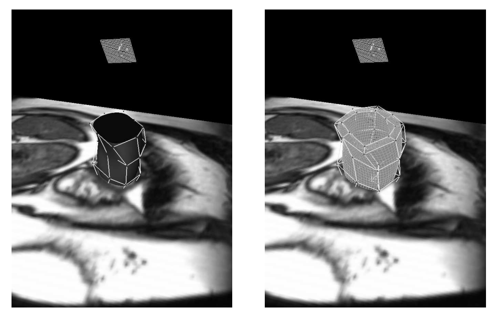
Example



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

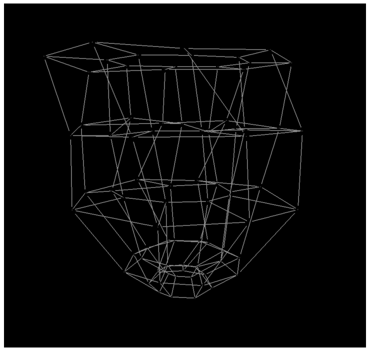
Lattice construction



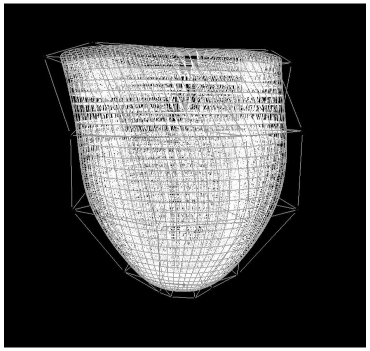
Motion tracking using registration

- 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

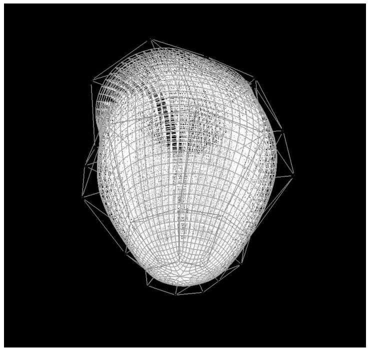
Preliminary results



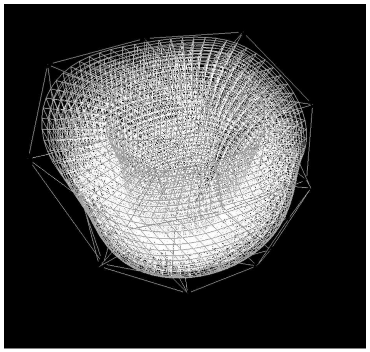
Preliminary results



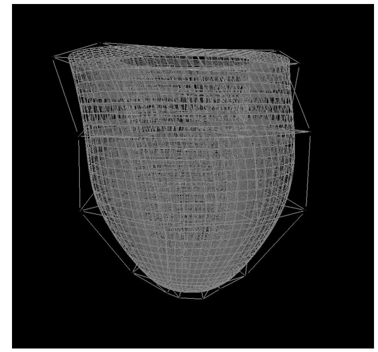
Preliminary results



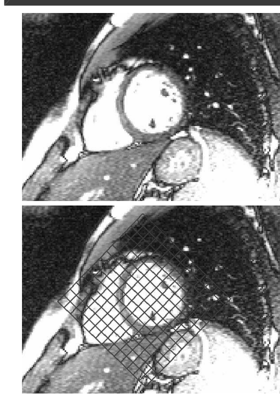
Preliminary results

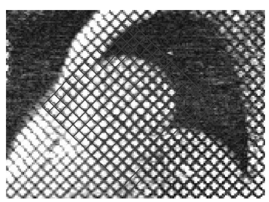


Preliminary results



Comparing cardiac motion from untagged MR vs. tagged MR





Comparing cardiac motion from untagged MR vs. tagged MR

Tagged

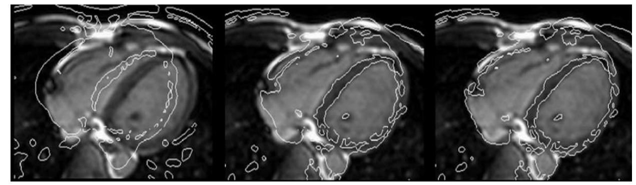
Untagged

Respiratory motion correction

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

Respiratory motion correction

Maximum inhale vs maximum exhale



No registration | Rigid registration | Non-rigid registration

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

Overview

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

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

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