Strategies for dealing with moving and deforming tissue in image acquisition and image guided interventions

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Why is moving and deforming tissue a problem?

Image guided surgery & Pathology correlation

External beam therapy

Needle placement for biopsy & therapy delivery
Strategies for dealing with structures moving between plan and surgery, therapy, intervention

– Ignore it
– Use intraoperative imaging & sensing
  • Different dimensionality
– Model deformation
– Learn motion
Dealing with motion during intra-operative imaging and during the intervention itself

• Deformation caused by the intervention itself
  – Brain, breast, prostate

• Intrinsic motion
  – Cardiac, respiratory, gut peristalsis
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Image-guided Neurosurgery using interventional MR

- Preoperative data acquisition
- Surgery Planning

- Patient Registration
- Planning in OR
- Intraoperative data acquisition
- Intraoperative navigation

- Postoperative data acquisition
- Postoperative visualization

Diagnostics, decision making and preoperative planning

Quality control and evaluation of treatment
Aims

• Improve surgical outcomes in patients with low grade gliomas using MR techniques pre and intra-operatively.
• Improve surgical outcomes for epilepsy patients by avoiding eloquent areas and minimising temporal lobe resection.
• Estimate and compensate for tissue and structure deformation during surgical interventions.
• Establish and validate a comprehensive set of imaging protocols for pre-operative and intra-operative imaging.

Example of displacement of the pyramidal tract (in blue) caused by low grade glioma.
iMRI facility at NHNN

Scanner dockable operating table

5 Gauss line
Image registration is a core underpinning technology: From Free-Form Deformation (FFD) to Fast Free-Form Deformation (F³D)

Modat et al Computer Methods and Programs in Biomed (2010)
Rueckert et al IEEE-Trans Med Imag (1999)

- Update all control points for each resampling
- Parzen Window estimation of Joint Histogram
- Convolution of gradient field of the cost function (NMI)
- Conjugate Gradient Optimisation
- 10 fold speed up from CPU to GPU implementation

Open source code available from [www.ucl.ac.uk/cmic](http://www.ucl.ac.uk/cmic)
Registration example - brain shift illustration

Daga et al. IEEE TMI 2011
Integrated brain shift estimation workflow

Anatomical and Diffusion images can be acquired during surgery.

Near real-time dual channel non-rigid registration
Breast Cancer

Difference of original images

Difference of aligned images

Rueckert et al IEEE-Trans Med Imag, 1999
Multimodal Breast Imaging, Image Guided Biopsy and Image Guided Lumpectomy

X-ray mammography to MRI registration
MRI to MG Registration: Example execution

Target Mammogram
Deforming MRI
Simulated Projections

HAMAM
MRI to MG Registration: Example execution

Target Mammogram
Deforming MRI
Simulated Projections

HAMAM
Simulation gives 3.8mm TRE

MRI to MG Registration: Example execution

Target Mammogram  Deforming MRI  Simulated Projections

HAMAM
Annotation from enhancement in DCE-MRI (overlayed in green) on X-ray mammogram (annotated in red)

T. Mertzanidou et al Medical Image Analysis Analysis 2012 (in press)

Validated using lesions annotated on mammograms

Mean accuracy:
Affine on 49 patients 13.1mm

Biomechanically informed on 5 patients 7.6mm

Mertzanidou IWDM 2012
Compensation for Deformation in Image Guided Surgery:

Biomechanical model registration of prone/supine MRI

Biomechanical model registration of prone/supine MRI

Han et al. (2010) IWDM, Han et al (2011) ISBI
Guidance for breast surgery

Carter et al. MIAR 2006, MICCAI 2008
Prostate Cancer: Image guided biopsy and focal ablation

Mark Emberton, Hash Ahmed, Dean Barratt, Yipeng Hu

Ahnmed et al Lancet Oncology 2012
Prostate cancer: the need for image registration

MRI (pre-therapy)
- T2
- DCE
- ADC

MRI (post-therapy)

CT + RT plan

TRUS

Biopsy

Histology
Real-time tracking of the prostate using US and MRI

PRE-PROCEDURE

Reference Shape

Deformed Shapes

MRI

DURING PROCEDURE

Deformation modeling

Register

Patient-specific SPSM

PRE-PROCEDURE

DURING PROCEDURE

Simulation No. 1

NiftySim
Automatic generation of deformable organ models

Subject | MRI | Ref. Shape | Deformation modelling | Deformed Shapes
--- | --- | --- | --- | ---
1 | ![MRI Image] | ![Ref. Shape] | ![Deformation Modelling] | ![Deformed Shapes]
2 | ![MRI Image] | ![Ref. Shape] | ![Deformation Modelling] | ![Deformed Shapes]
... | ... | ... | ... | ...| 100 | ![MRI Image] | ![Ref. Shape] | ![Deformation Modelling] | ![Deformed Shapes]
New | ![MRI Image] | ![Ref. Shape] | ![Deformation Modelling] | ![Deformed Shapes]

Training Data

Generative SPSM

Patient-specific SPSM

Equivalent

Hu et al. Medical Image Analysis, 2012
Rigid versus non-rigid registration

Original MR image

Rigid

Non-Rigid

Warped MR image

Registered

TRUS image

Hu et al. IEEE TMI, 2011
Prostate Biopsy System Design

- Not reliant on expertise
- Automatic, deformable image registration
- < 3mm error
- Widely compatible
- Diagnosis and therapy
- Low-cost
Colon Cancer
Polyp detection in CT Colonography

- CT imaging now is a reliable alternative to the more traditional method of colon cancer detection: colonoscopy.

- One drawback to this new technique of colon CT imaging: the colon is extremely flexible.

- Stool and fluid residues creates challenges to detect polyps reliably.

- Changing body positions is necessary.

- Comparing both raw CT images is often performed manually by a radiologist.
Prone to Supine CT Registration

- mathematical simplification process (3D->2D)
- cylinders
- do the polyp locations match between images?
Establishing correspondence
85% of 1175 manually identified landmarks, on 8 cases, identified to correct haustral fold, further 15% to within one haustral fold
(Roth et al Medical Physics 2011)
The Future: Combining optical imaging with CT


Ileocecal valve

[Gray]
Dealing with motion during intra-operative imaging and during the intervention itself

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Transcostal High Intensity Focussed Ultrasound of Lesions of the Liver

Breathing Patterns from Real-time MR THRIVE and motion modelling

Erik Rijkhorst et al IPCAI 2010, MICCAI 2011
Transcostal High Intensity Focussed Ultrasound of Lesions of the Liver

Erik Rijkhorst et al IPCAI 2010, MICCAI 2011
HIFU heating of *moving* liver tissue

- **Thermal model, bioheat equation:** *(Pennes 1948)*
  \[
  \rho C \frac{\partial T}{\partial t} = K \nabla^2 T - W_b C_b (T - T_b) + q(t)
  \]

- **HIFU energy density** \( q(t) \)
  - Rayleigh integral for spherical bowl transducer. *(Meaney et al. 1998)*
  - Translation according to motion model.

- **Example of continuous heating** for 8s, corresponding to 2 breathing cycles.

Rijkorst et al MICCAI 2011
Lung Radiotherapy:
How to compensate for tumour motion?
Widen margins, Gate or Track

In-room stereo video, KV and MV imaging with linac
Motion modelling in lung radiotherapy


Model error 1.7mm (RMS), slice thickness 1.5mm (McClelland et al AAPM 2008)
Motion models compared to 4DCT

Model error 1.7mm (RMS), slice thickness 1.5mm
(McClelland et al Med Phys 2006, AAPM 2008)
Inter-fraction variation

Session 1 Coronal View

Session 2 Coronal View

Sagittal view: Session 1 - Red, Session 2 - Cyan

Coronal view: Session 1 - Red, Session 2 - Cyan

McClelland et al Phys Med Biol 2011
Motion leads to distortion and artefact

Motion leads to blurring
Abdominal CT 1980 – 2006

EMI CT5005 – 70sec, 13mm slice

Philips 16 slice, 0.5 sec, fluoro CT for needle placement
Ungated Reconstruction
Courtesty: Michael Grass (Philips) and Jamie McClelland (UCL)
Motion Induced Artefact in MR

Bulk motion of head

Respiratory motion
Motion compensation during reconstruction

Odille et al., 2008
MRM, 59:1401-1411
White et al, 2009
MRM
GRICS: Generalized Reconstruction by Inversion of Coupled Systems

\[
\begin{align*}
    s &= E(\alpha) \rho_0 \\
    \varepsilon &\simeq R(\rho_0, \alpha) \delta \alpha
\end{align*}
\]

Solution method:
- Multi-resolution, fixed-point iteration method
- Over-determination by acquiring multiple respiratory phases

Odille et al., 2008, MRM, 59:1401-1411
Free-breathing liver MRI (3D)


- 4 scan repetitions, SENSE factor 8
- 236x208x112 matrix, 1.7x1.7x3.4 mm³
- Splitting: 59 slabs of 13.6 mm (6.8 mm + 6.8 mm overlap)

Uncorrected (SENSE)

Parallel GRICS:

Single thread GRICS: 5.3 hours
Parallel GRICS: 17.4 min (18x speed-up)
Prior information assisted compressed sensing reconstruction: k-t group sparse reconstruction - exploiting x-f sparsity

Using CS as motion estimator
Use CBCT to update motion model

Can be difficult to see tumour in CBCT projections

And tumour can appear ‘blurry’ in CBCT reconstructions

Example from simulated data
McClelland et al ESTRO 2011, Martin et al MMBIA 2012
Developed method to ‘enhance’ appearance of tumour in CBCT projections
Results

Real phantom results

Simulated patient results

- Converged after 5 iterations
- Mean error reduced from 4.1mm to 1.0mm
- Max error reduced from 16.5mm to 4.6mm
Determining and correcting for cancer tumour motion during stereotactic body radiotherapy

James Martin and Jamie McClelland
Intelligent Imaging of Repetitive Motion

Andy King (KCL)
Computational challenges

- “Real-time” imaging and motion compensation
- “Real-time” computational modelling and registration
- Strategies for combining very large scale computation with real-time application
- Efficient workflow!

- Applications and toolkits for translational research
  - Open source
  - Usable by clinical research fellows, technologists (not just developers!)
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<tr>
<th>Technologies</th>
<th>Applications</th>
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<tr>
<td>• Non-rigid 3D-3D registration</td>
<td>Interventional MR guided neurosurgery</td>
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<td>• Reducing dimensionality (non-rigid tube embedded in 3D)</td>
<td>Colon polyp detection</td>
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<td>• Non-rigid 3D to projection</td>
<td>Image guided breast biopsy and lumpectomy</td>
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<td>• Biomechanical modelling</td>
<td>Lung radiotherapy</td>
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<td>• Learnt repetitive motion</td>
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<td>• Learnt deformation fields</td>
<td>Image guided prostate biopsy and focal ablation</td>
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<td>• Compressed sensing</td>
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Code development in CMIC
Open Source – download from [www.ucl.ac.uk/cmic](http://www.ucl.ac.uk/cmic)
Thank you et Merci

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