The ACPSEM Medical Image Registration Special Interest Group (MIRSIG) Online Webinars

This seminar (1200, Tue 4th August 2020) is chaired by Michael Jameson.

- Talk 1: **New Advances in Image Registration**

Presented by Jason Dowling

Webinar activities!!

-Use the "Q&A" to ask questions!

Liver Poll!

Poll information will be used to confirm CPD, so it is important to participate!

Post webinar survey!

Please answer survey when email is sent

Seminar material available online!

Please see https://www.acpsem.org.au/About-the-College/Special-Interest-Groups/MIRSIG

Be more involved!

1. MIRSIG welcomes professions from all disciplines, including radiation therapists and radiation oncologists
2. Sign up to the MIRSIG mailing list (https://www.acpsem.org.au/Home , click myACPSEM, click speciality groups, tick MIRSIG)
3. Join MIRSIG as a member, email mirsig@acpsem.org.au

Australia's National Science Agency

New Advances in Image Registration

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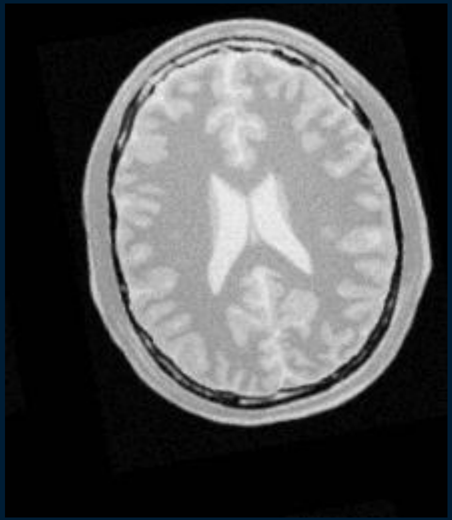
ACPSEM Medical Image Registration Special Interest Group
4th August 2020

Learning objectives

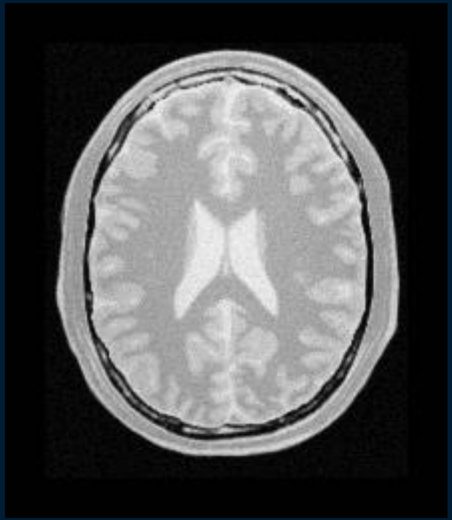
1. Identify the **components** of image registration algorithms
2. Describe how **rigid, affine** and **deformable** registration works
3. Identify **advanced applications** for registration (including atlases)
4. Recognize the elements of **advanced image registration** (e.g. deformation with masking or iteration, deep learning)
5. Describe ways to detect and identify causes of **registration failure**

What is image registration?

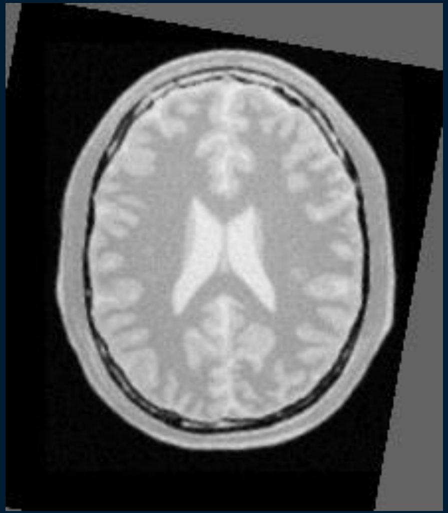
The process of estimating an optimal transformation to map points between two images.



Moving Image



Fixed Image



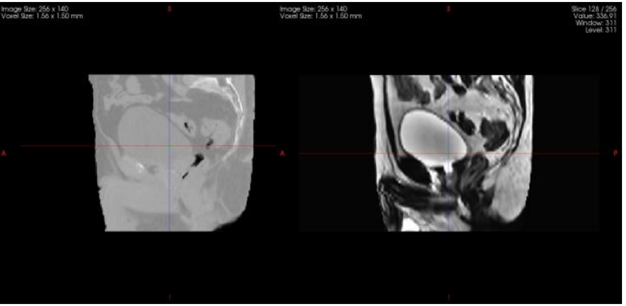
Registered Moving Image

Source: Kitware Inc. ITK registration Methods

Image Types

- Mono modal (e.g.. CT->CT, MR->MR)
- Multi modal (e.g.. MR->CT, US->MRI)

- 2D -> 3D (pathology->MRI, x-ray->CT)
- 3D->4D (lung CT)
- 3D->2D (cine MRI)



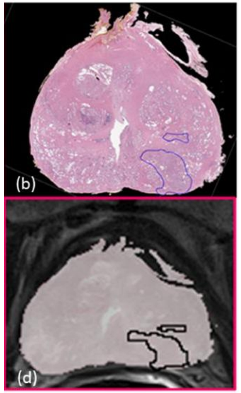


Image: Li, et al. (2017) Sci Rep, 8717

Registration Types

Registration: same patient

Normalisation: inter patient

Manual

Point/ landmark/ features

Surface based (eg. ICP)

Finite Element Method

Intensity

This talk will mainly consider 3D intensity based image registration

What is deformable registration?

- Rigid (rotation, translation) (6 D.O.F.)
- Affine (rigid + scale and shear) (12 D.O.F.)
- **Deformable (aka non-rigid or elastic) (3N D.O.F.)**

- Plus others (Piecewise affine, etc)

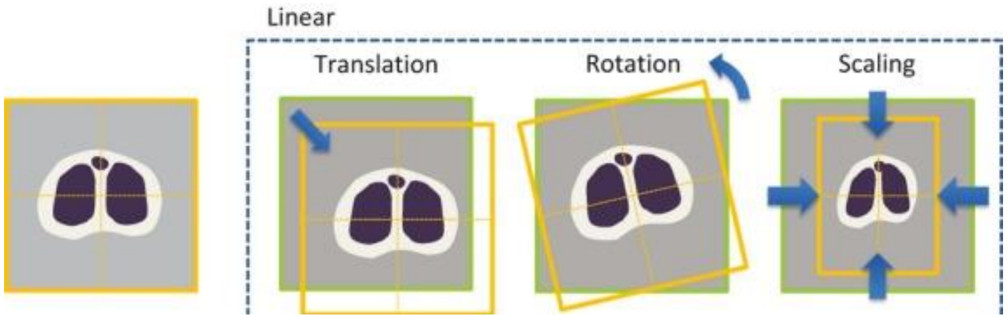


Image: Uchida S, 2013, Dev Growth Differ. 55(4):523-49

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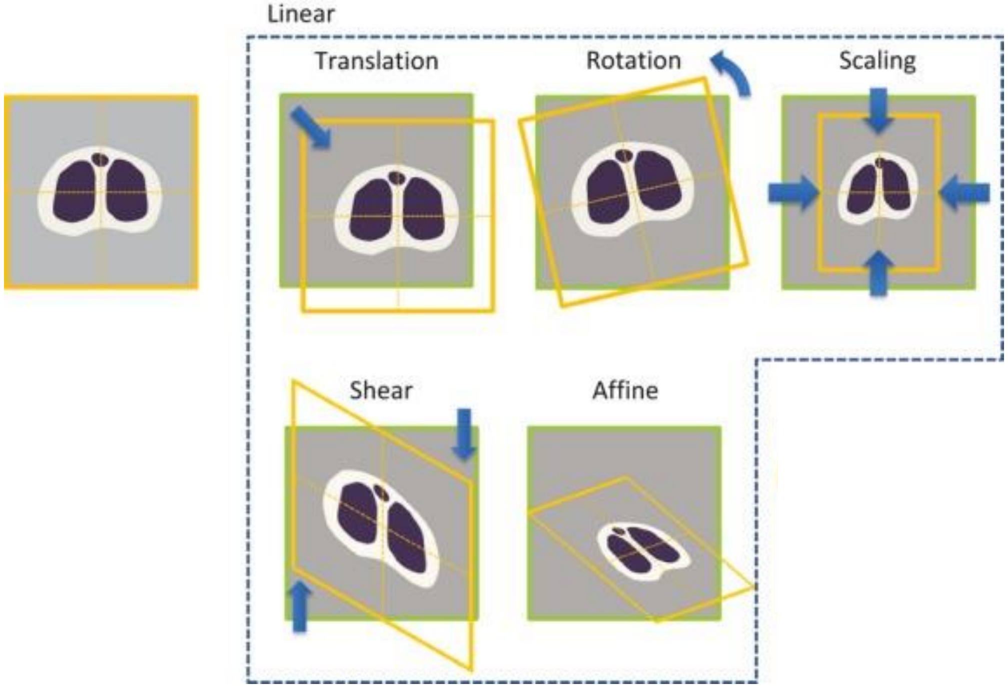

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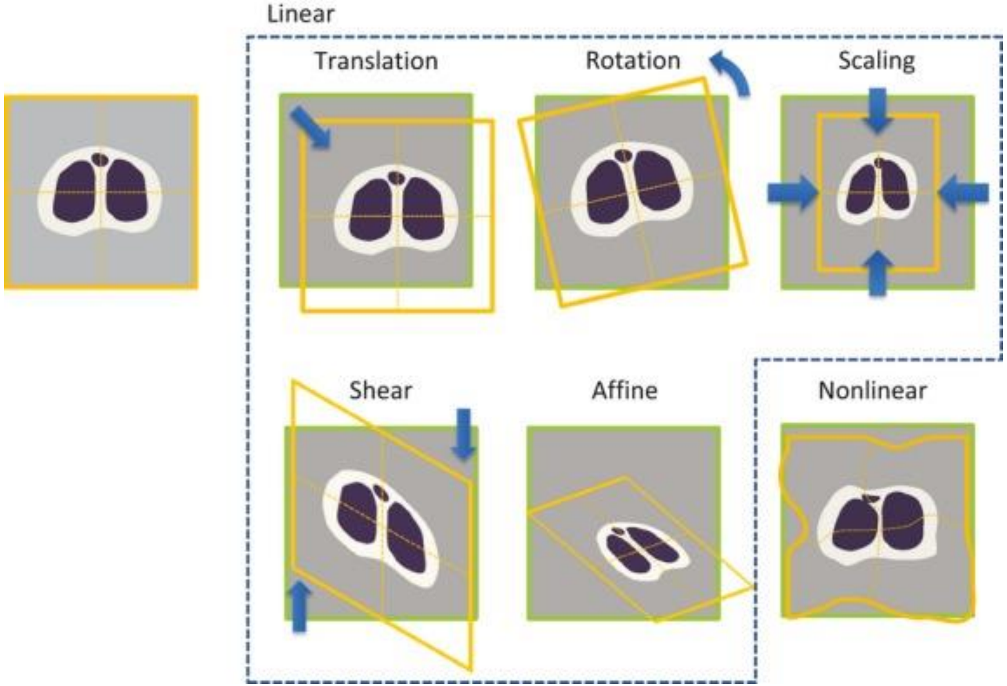


Image: Uchida S, 2013, Dev Growth Differ. 55(4):523-49

Image registration components

Metrics
Transform
Optimizer
Interpolator

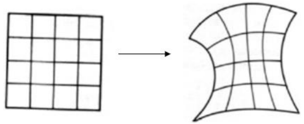
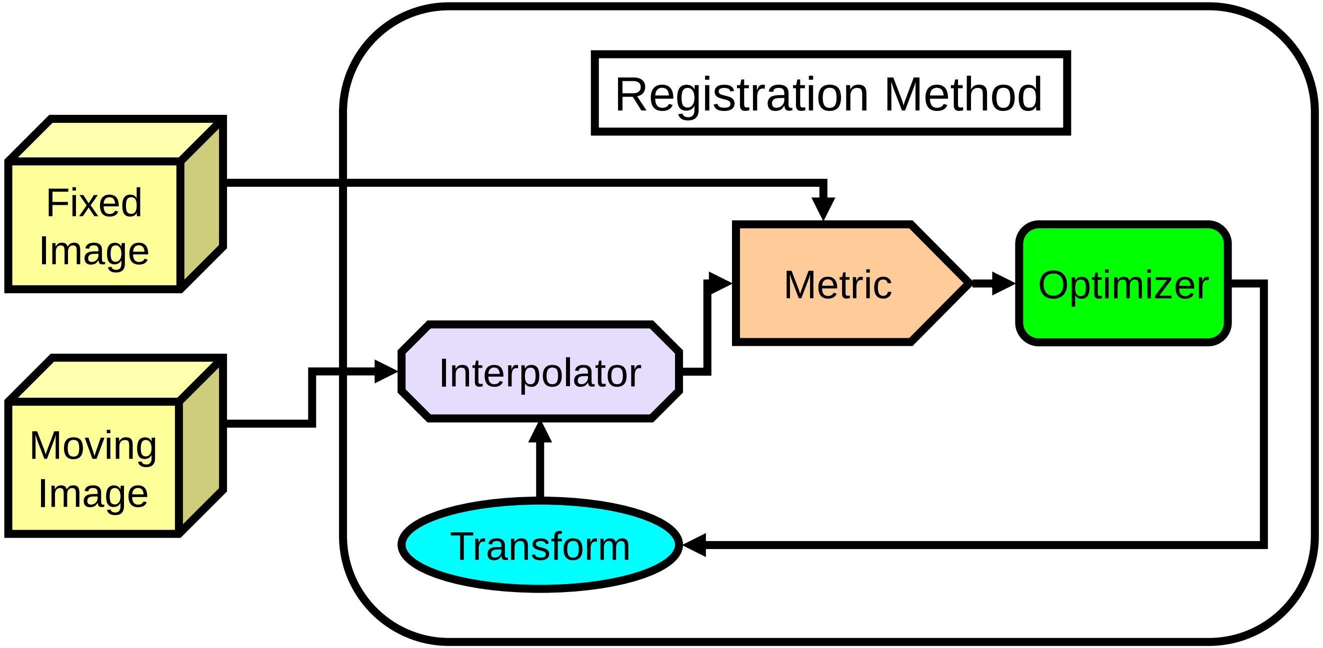
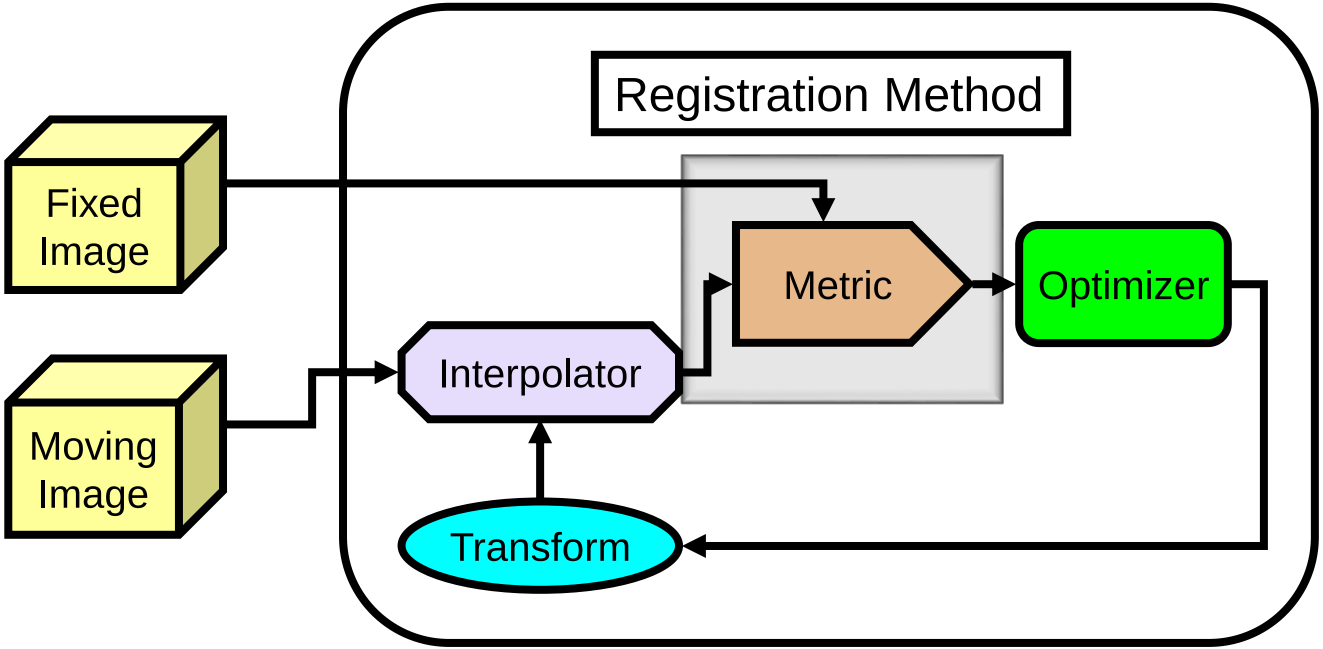


Image Registration



Source: Kitware Inc. ITK registration Methods

Similarity metrics



Source: Kitware Inc. ITK registration Methods

Similarity Metrics

- The **perfect** metric
  - Will be minimised for correctly aligned images
  - Is smooth, convex
  - Can be computed quickly
  - Is differentiable

- Sampling
  - Using all voxels can be time consuming, so common to use a subset (sampled randomly, selected on a uniform grid, only on edges, …)
  - Also masks can be used to select a region of interest or to avoid aligning artificial edges in the images
- Regularisation
  - For example penalize the compression or expansion of tissues

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- Mean Squared Error
  - Easy to code and fast to compute
  - Optimal value of the metric is zero
  - Assumption that the intensity representing the same point in both images will be the same
  - <u>Only suited to mono-modality registration</u>

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- Normalised Cross Correlation
  - Frequently used for template matching
  - Optimal value -1
  - Expresses the linear relationship between voxel intensities in the two volumes. Misalignment between the images results in small measure values.
  - This metric produces a cost function with sharp peaks and well-defined minima. On the other hand, it has a relatively small capture radius.

  - Only suited to mono-modality registration
  - Particularly well suited for intra-modal CT

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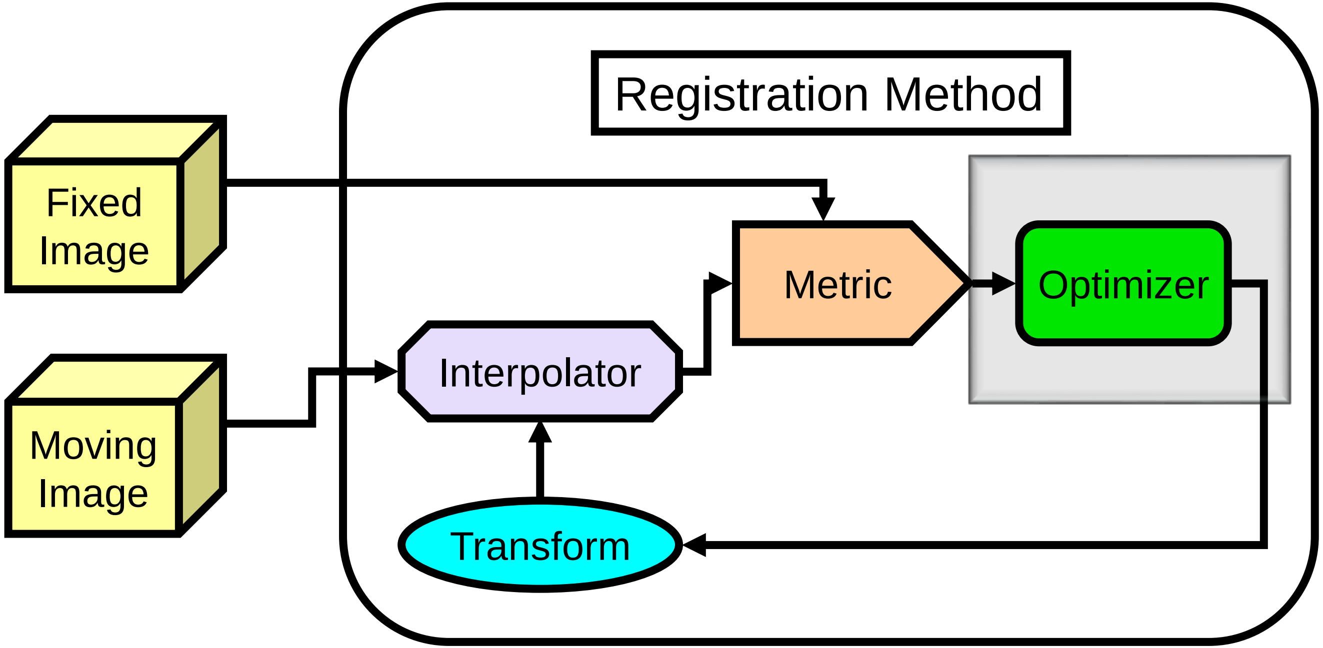
- Mutual Information
  - Intensity only metrics (like MSE) will fail as the physical principle for the imaging modalities is different (there is no reason why a bright voxel in one volume should correspond to a bright voxel in the other volume).
  - Measures how much information one random variable (image intensity in one image) tells about another random variable (image intensity in the other image).
  - Can be a problem if the joint histogram is sparsely populated, for instance due to lacking information in one of the images, the measure is likely to fail.
  - Suited to mono- and multi-modality registration

Optimisation

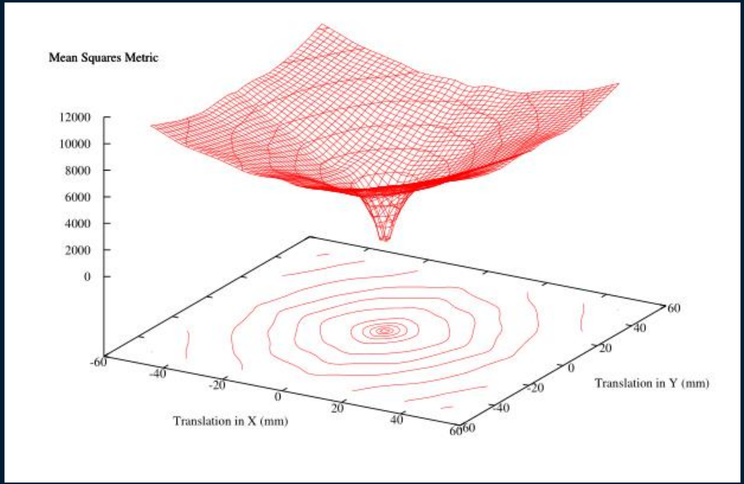


Source: Kitware Inc. ITK registration Methods

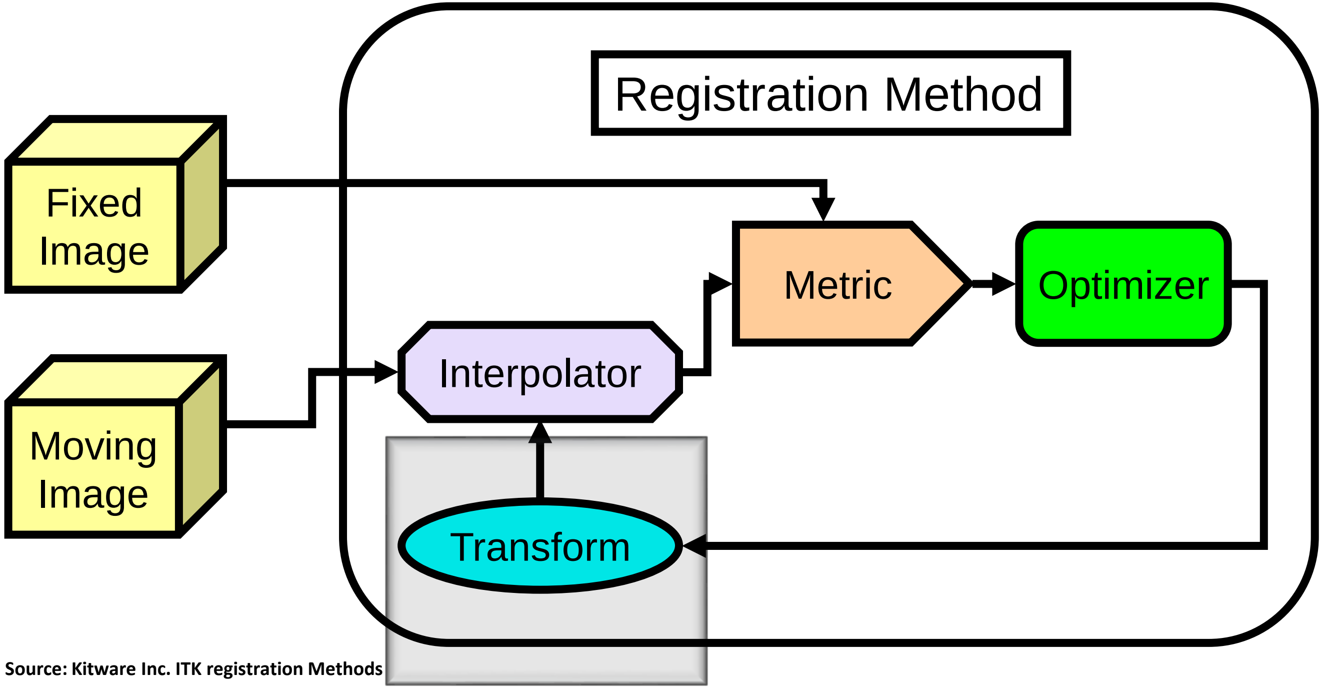
Optimisation

- The metric uses information from the fixed and moving image to compute a similarity value. The derivative of this value tells us in which direction we should move the moving image for better alignment.
- Huge number of algorithms. Gradient descent (or variants) common
- “Salad bowl and a marble”
- The metric is only calculated at discrete points, we don’t know if this a local minimum or the absolute optimum

- Learning rate/Step size
- Step size relaxation rate (eg. 50%)
- Iterations
- Convergence minimum value



Transforms



Source: Kitware Inc. ITK registration Methods

Transform types

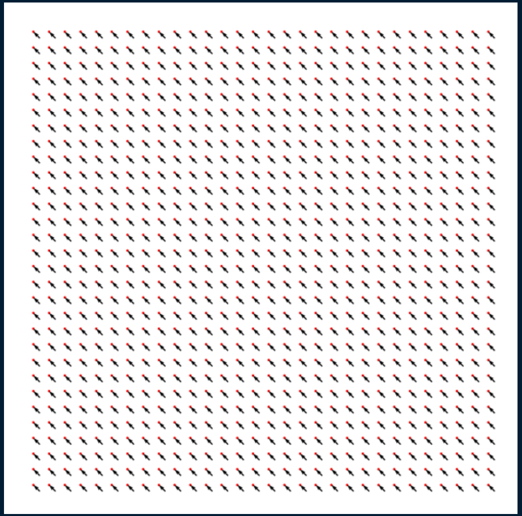
Global

- Rigid (rotation, translation)
- Affine (rigid + scale and shear)

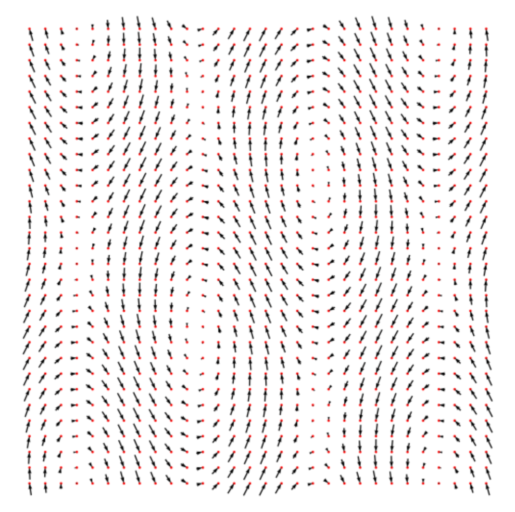
Local

- Free form deformation
  - Deform an object by manipulating an underlying mesh of control points
  - Ideal for mono and multi-modal registration
- Diffeomorphic Demons
  - Assumes that voxels representing the same anatomy in both images have the same intensity
  - Gradients (edges) are important voxels
  - Mono modal

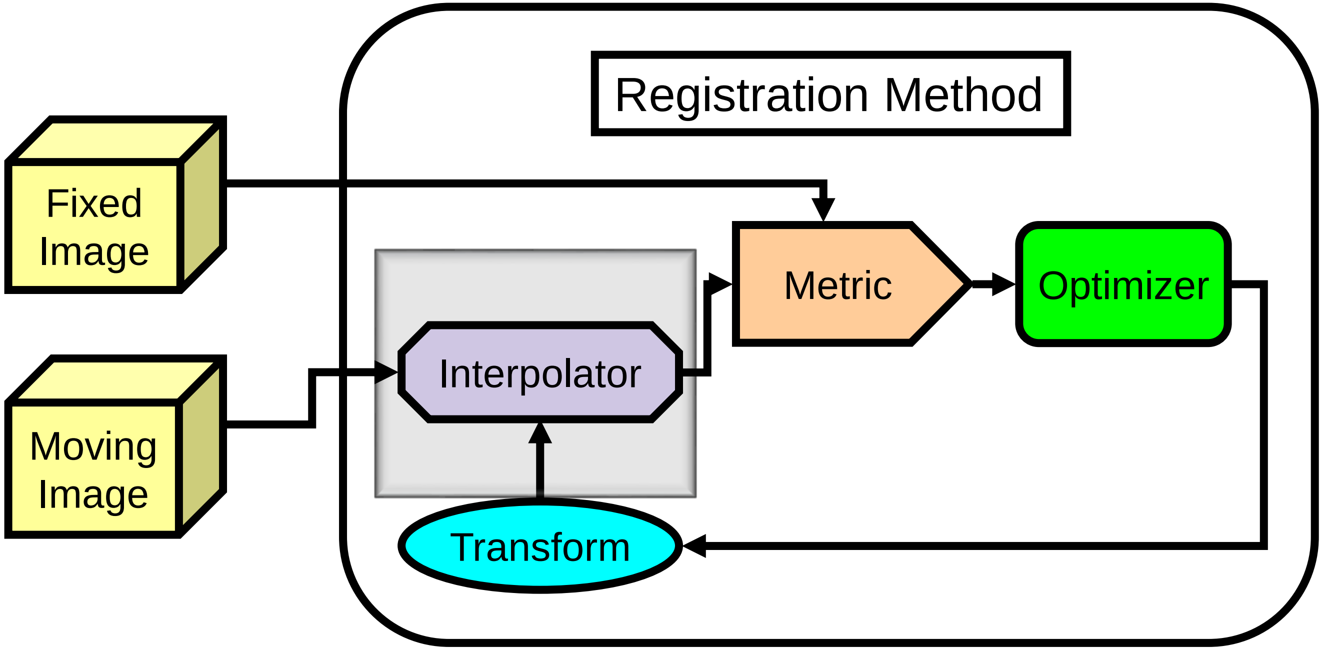
Rigid



Deformable



Interpolation



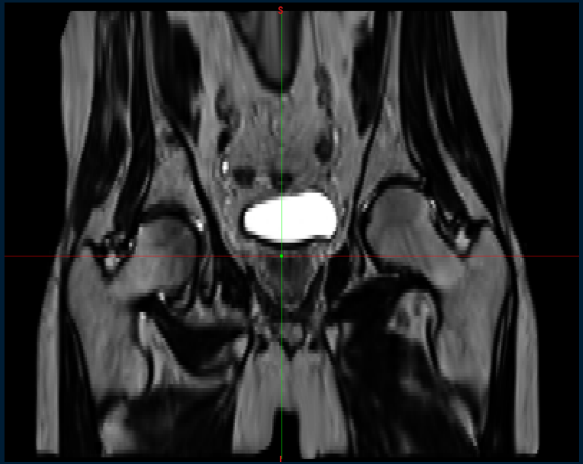
Source: Kitware Inc. ITK registration Methods

Interpolation

- When points are transformed they are generally mapped to a non-grid position. Interpolation estimates the image intensity at the mapped position.
- Also needed for resampling (changing volume spacing, size, etc)
- Nearest Neighbour interpolation:
  - take the closest voxel from the moving image.
  - Will not change the range of values in the registered image. Necessary for mapping contours
- Trilinear interpolation
  - Linearly weight with the surrounding eight voxels. Assumes intensity varies linearly between grid positions

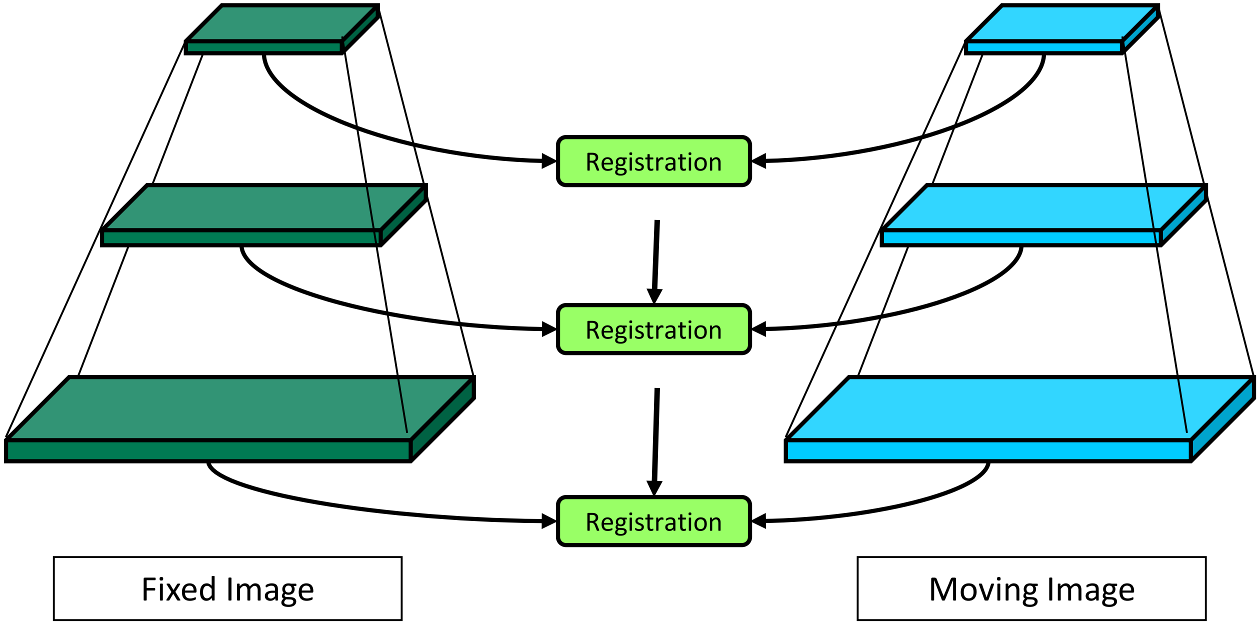
Nearest Neighbour

Linear



Multi-resolution Registration Framework

- Improve speed, accuracy and robustness



Source: Kitware Inc. ITK registration Methods

Registration issues

Some common issues

Image preprocessing

Deformation field analysis

Validation

Rigid structure deformatrion (CT)

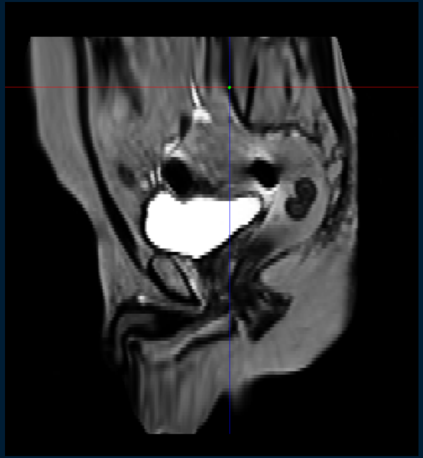
Common Issues

- Rigid Registration has failed
- Field of view differences (see right)
- Problems with registration components (wrong metric, transform or optimizer settings)
- Anisotropic data (6mm slice thickness, etc)
- Artefacts (eg. motion)

Moving (MRI)

Target (CT)

Deformable Result

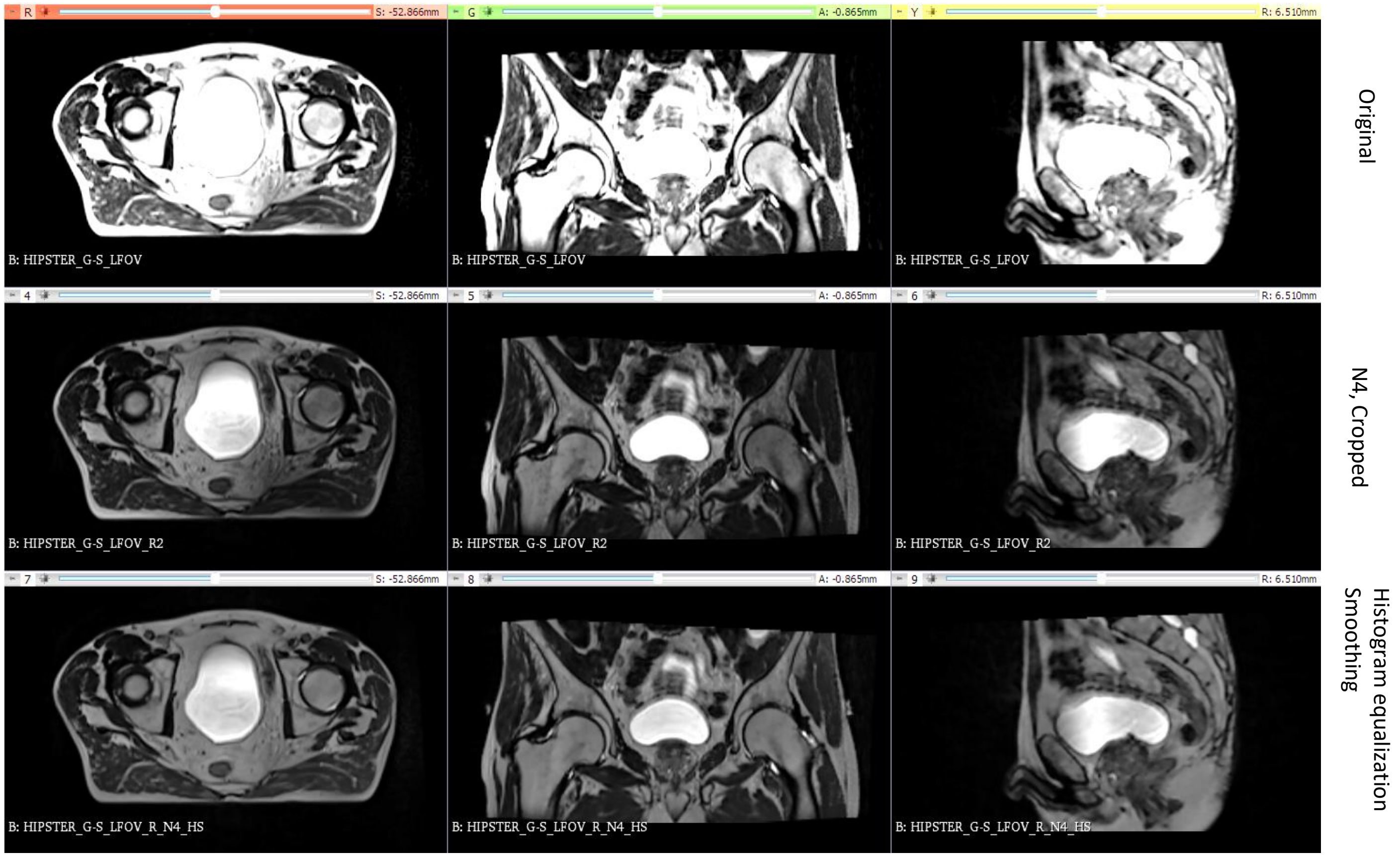


Preprocessing

Preprocessing images prior to registration can improve accuracy:

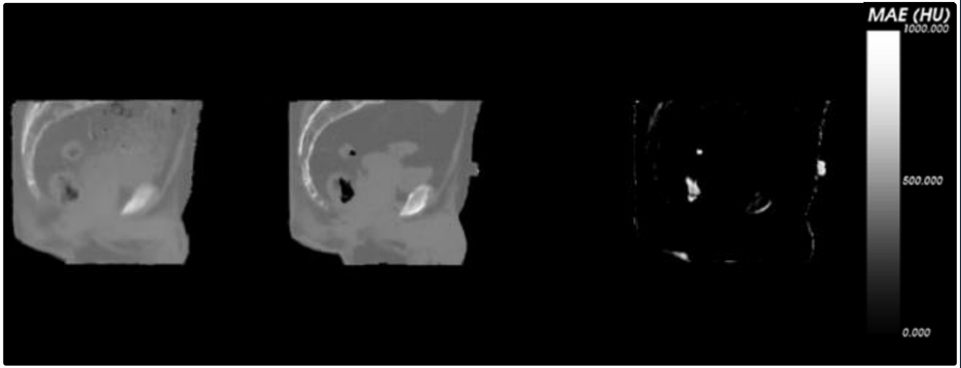
- Masking (e.g. Remove couch from CT)
- Cropping (e.g. Create bounding box between lungs for heart)
- Resampling (e.g. try to ‘correct’ anisotropic data)
- Noise reduction (e.g. smoothing filters)
- Reduce artefacts (e.g. intensity inhomogeneity in MRI, streaking artefacts on CT)
- Histogram equalization (to a base volume)

Preprocessing (MRI)



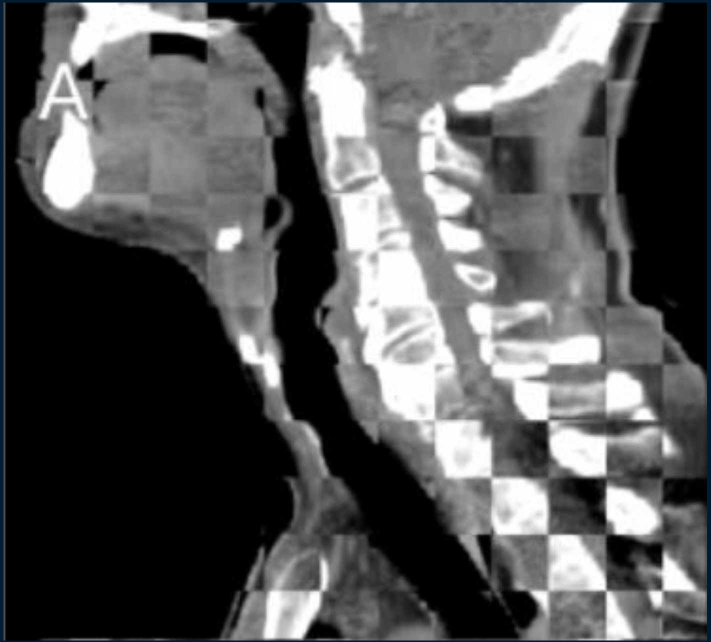
Validation

- Qualitative
  - Checkerboard
  - Overlap
  - Difference Image



sCT from MRI   Planning CT   Difference

Dowling et al. 2015. IJROBP

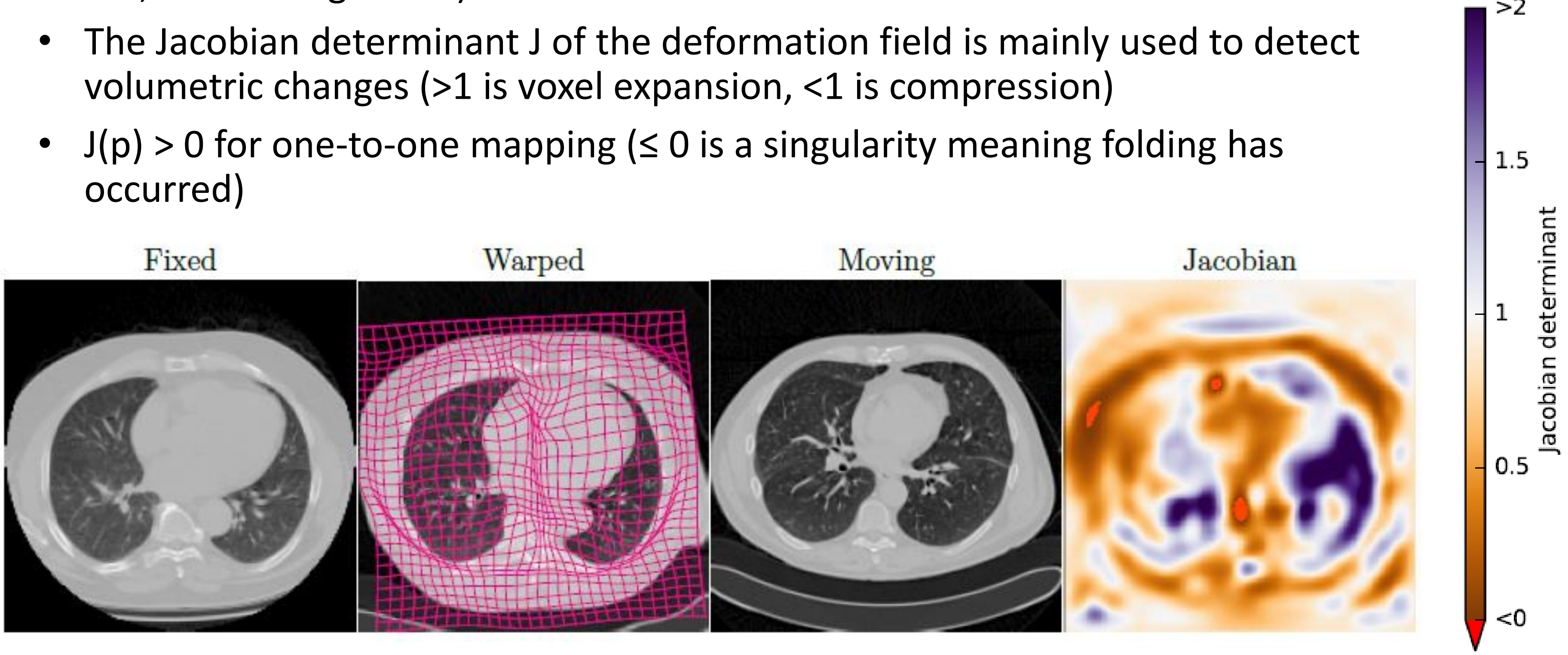


Checkerboard

Landry et al. 2015. Med Phys

Output from registration

- The deformation field itself can also be analysed (e.g Jacobian determinant and, vector magnitude)
- The Jacobian determinant J of the deformation field is mainly used to detect volumetric changes (>1 is voxel expansion, <1 is compression)
- J(p) > 0 for one-to-one mapping (≤ 0 is a singularity meaning folding has occurred)



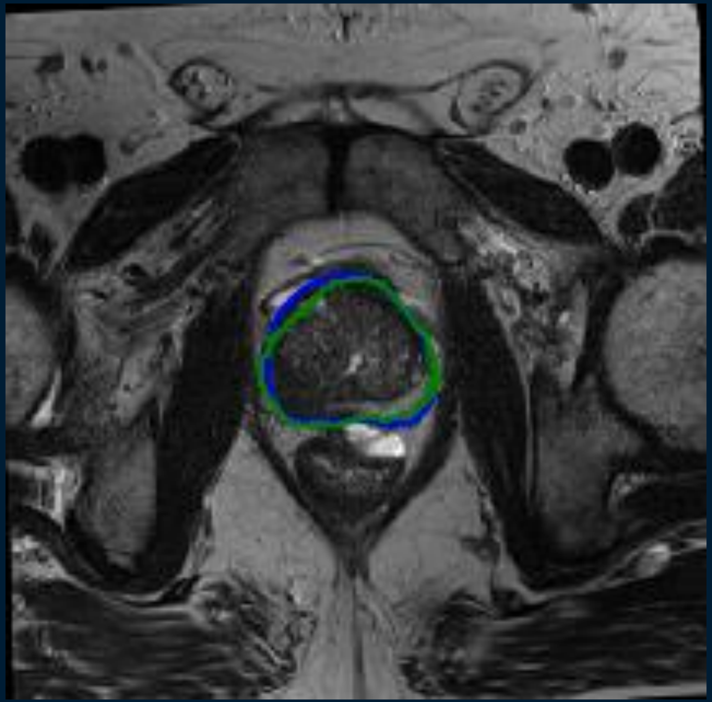
De vos et al 2019 Medical Image Analysis

Validation

- Quantitative
  - Target registration error (TRE)
  - Contour based overlap (Dice Similarity Coefficent, etc)
  - Jacobian (e.g. within structures)
- No validation measure is perfect
  - Best to combine measures
  - Segmentation + intensity
  - Intensity + Deformation

- Best method is to have a large number of densely distributed landmarks (identifiable anatomical locations) (Rohlfing TMI 2012)

DSC=0.89
MASD=1.31mm
Original volume: 53.44cc
Registered volume: 52.39cc



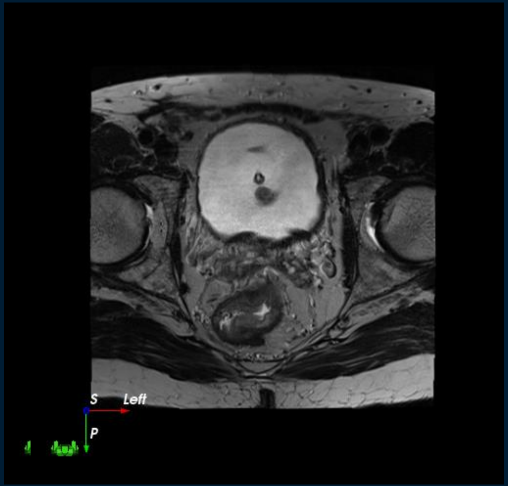
Original contour= blue ;
Registered contour= green

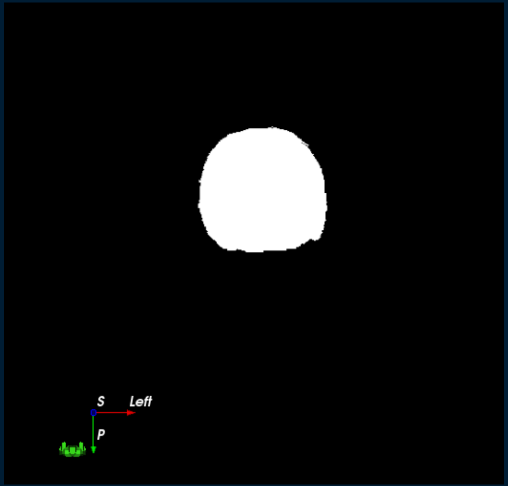
Advanced image registration

CSIRO Health and Biosecurity

Masking

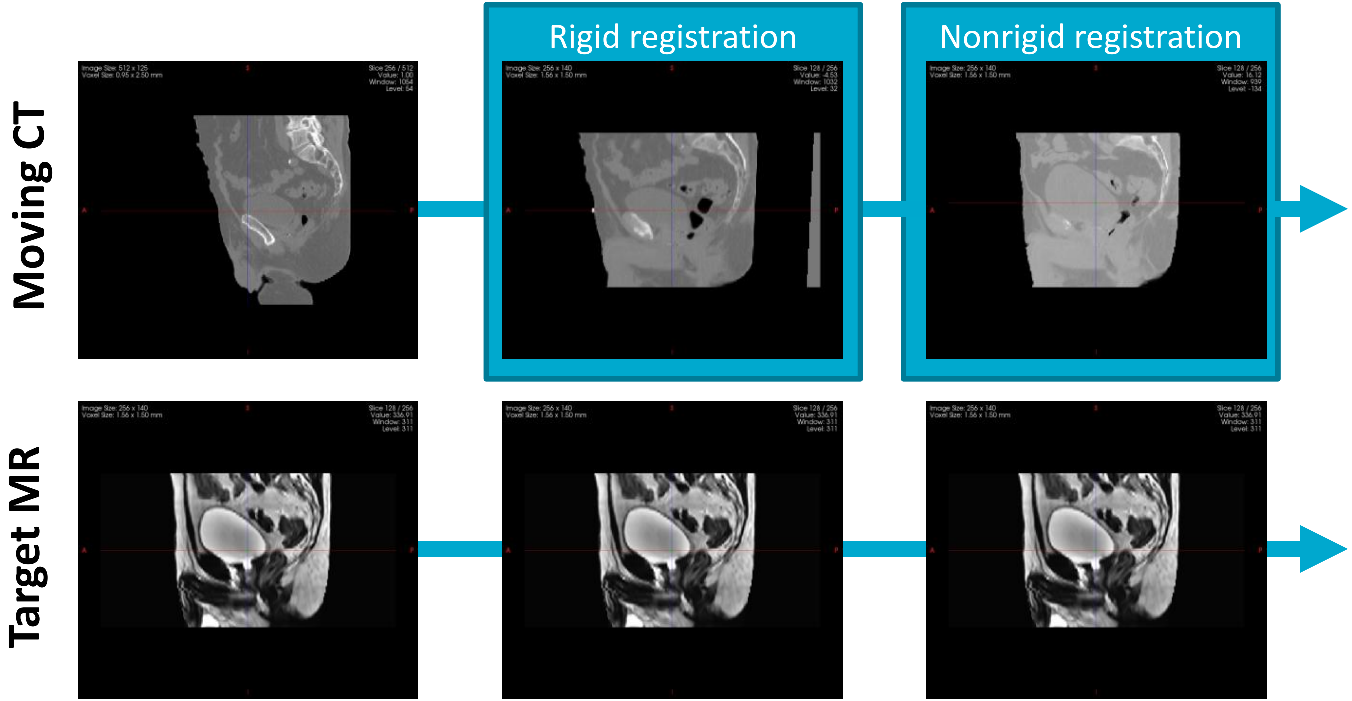
- The metric is generally sampled from both all voxels in both volumes
- Masking out regions can lead to improved results by enhancing
- A binary mask filled with 0s and 1s (only 1s are considered for the metric)
- Can restrict rigid structures (eg. aligned bone) from deformation with 0s
- Can use masks to remove artificial edges (e.g. from CT couch)





Structure guided registration (multiple DIR transforms)

(Note CT bladder)



Advanced applications for registration

Deformation and normative atlases for segmentation and shape quantification

CSIRO Health and Biosecurity

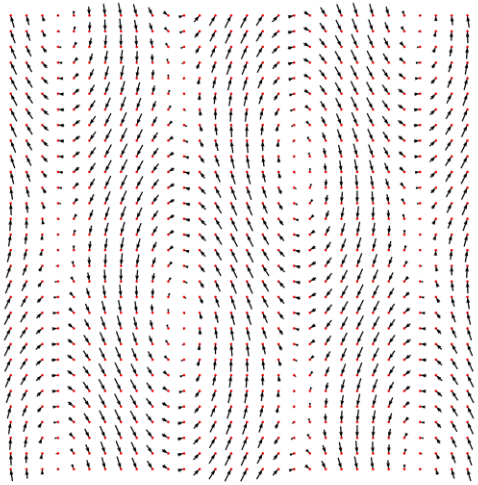
Output from registration

- Image resampled into target space (give example with size, spacing, origin, orientation)
- If global: transformation matrix

Sample rigid transform

0.999852	-0.0006606	0.0171537	-8.6275
0.00102579	0.999773	-0.0212404	-10.2279
-0.0171356	0.0212549	0.999626	-13.582
0	0	0	1

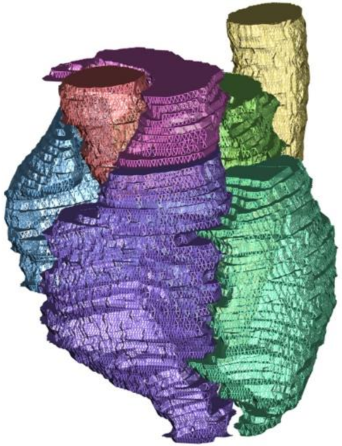
- If local: deformation field (usually)



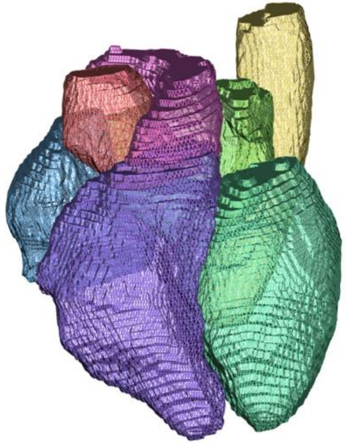
- **These files can be reused to resample (propagate) images, structures, dose, etc.**

Output from registration
Automatic Atlas Based Segmentation

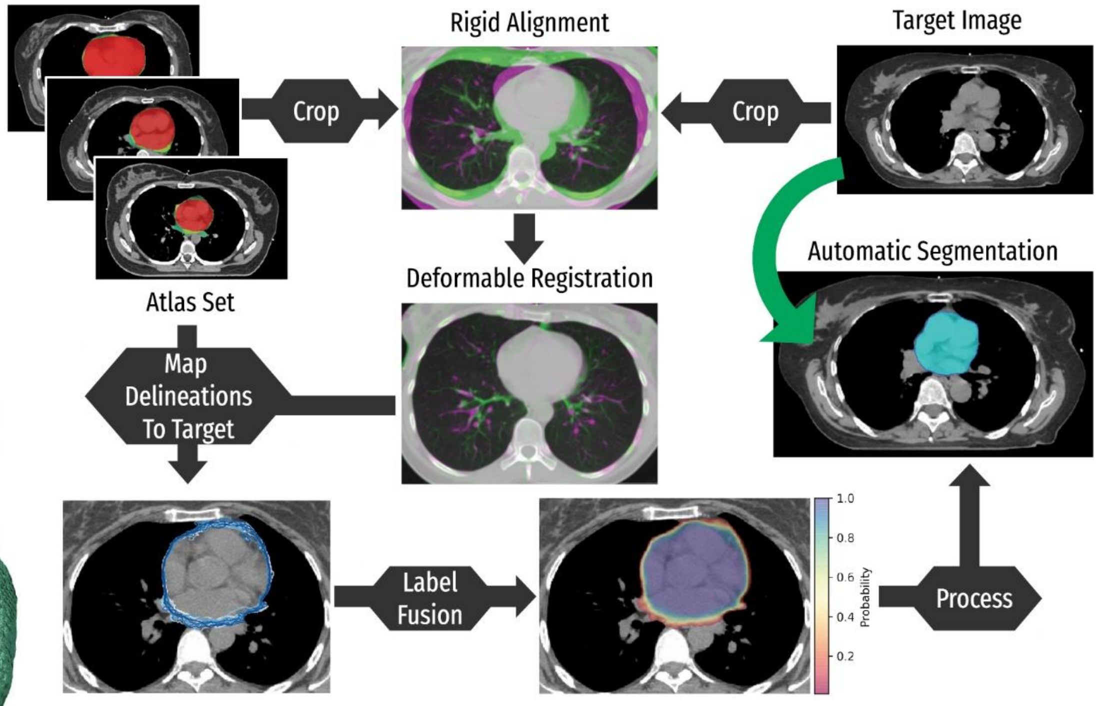
- Register one or more atlas scans to a new volume and propagate the labels (usually followed with a label fusion step)
- Quality of the training set, contours and registration accuracy are all critical



Manual Cardiac Contours



Atlas based auto-contours

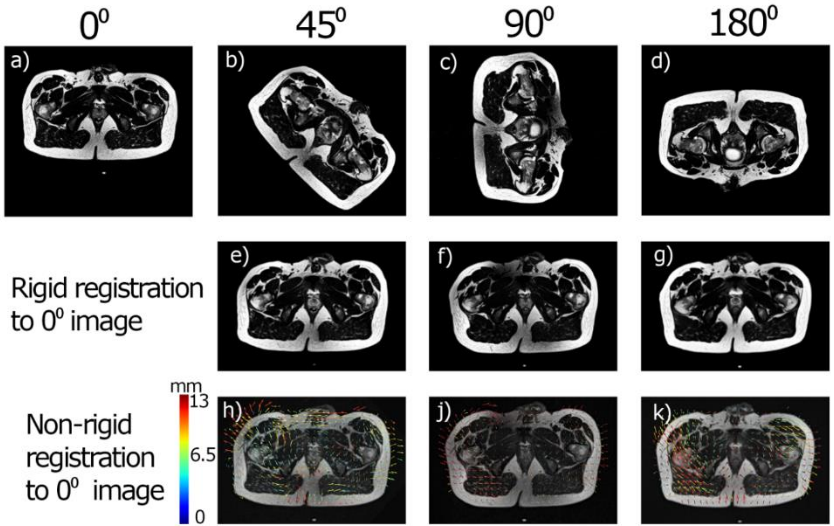


Finnegan et al. 2019. PMB

Output from registration

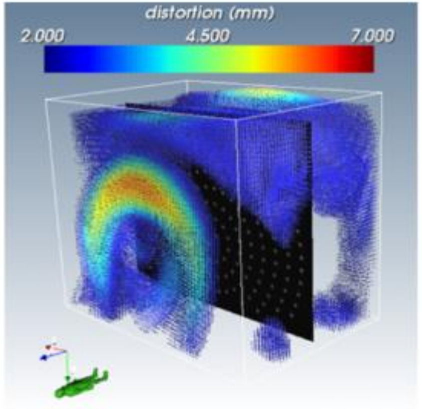
Analysis from deformation fields

Patient motion from rotating couch (MR Linac)



Whelan, et al. (2017) Med Phys

Geometric distortion (phantom)



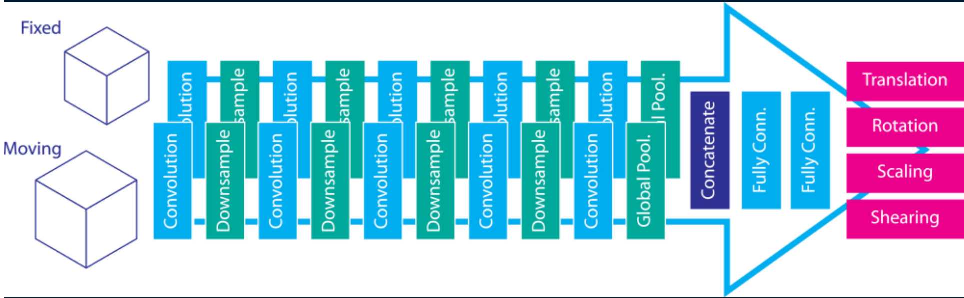
Walker et al. (2015) Med Phys

New developments

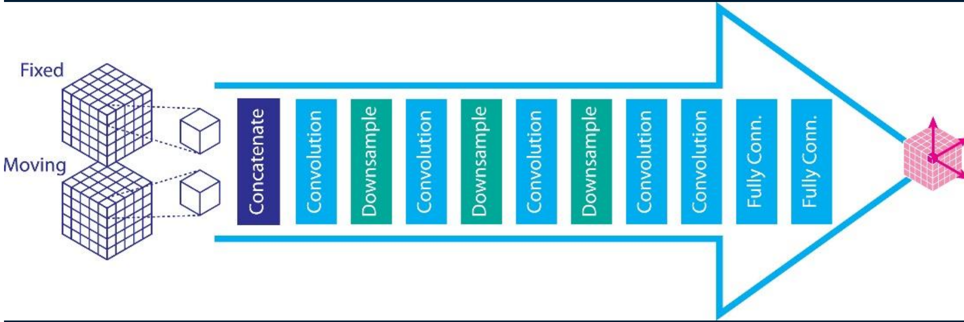
Deep learning

- Deep convolutional neural networks have had a huge impact on medical image segmentation
- There is a huge amount of interest in deep learning registration methods (particularly due to speed)
- Main approaches:
  - Supervised learning: use classical methods to get vector fields and train a CNN to learn these vector-field
  - Unsupervised learning: use a similarity metric between volumes

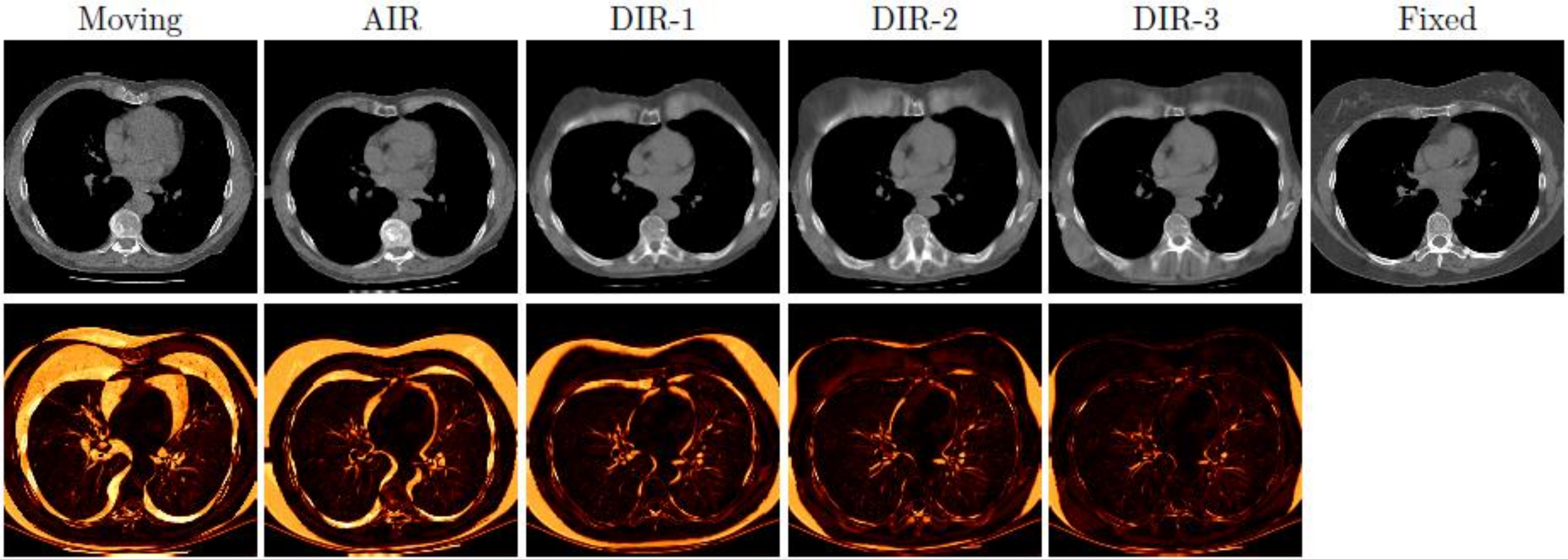
Rigid/Affine (different volume sizes)



Deformable registration



De vos et al 2019 Medical Image Analysis



Aorta		Dice	HD	ASD	Fraction folding (%)	Std. dev. Jacobian	CPU time (s)	GPU time (s)
Before registration		0.31 ± 0.21	32.62 ± 12.21	9.21 ± 4.53	–	–	–	–
SE	AIR	0.60 ± 0.19	25.81 ± 15.34	4.89 ± 2.36	–	–	3.73(0.26)	–
	DIR-1	0.69 ± 0.11	20.30 ± 13.26	3.39 ± 1.11	0.00 ± 0.00	0.19 ± 0.11	11.67(1.07)	–
	DIR-2	0.75 ± 0.08	21.26 ± 11.31	2.67 ± 0.87	0.00 ± 0.08	0.27 ± 0.13	14.83(3.37)	–
	DIR-3	0.77 ± 0.08	20.83 ± 11.81	2.45 ± 0.89	0.04 ± 0.19	0.30 ± 0.15	20.36(8.41)	–
DLIR	AIR	0.58 ± 0.16	26.79 ± 13.05	5.24 ± 2.19	–	–	1.02(0.29)	0.17(0.05)
	DIR-1	0.64 ± 0.11	21.68 ± 13.09	3.86 ± 1.74	0.00 ± 0.00	0.16 ± 0.09	3.85(0.99)	0.18(0.05)
	DIR-2	0.70 ± 0.10	19.95 ± 13.30	3.21 ± 1.15	0.00 ± 0.00	0.19 ± 0.10	8.18(2.03)	0.30(0.07)
	DIR-3	0.75 ± 0.08	19.34 ± 13.41	2.46 ± 0.80	0.75 ± 1.08	0.45 ± 0.21	15.41(4.38)	0.43(0.10)

De vos et al 2019 Medical Image Analy

CSIRO

ITK-based software for registration and visualisation

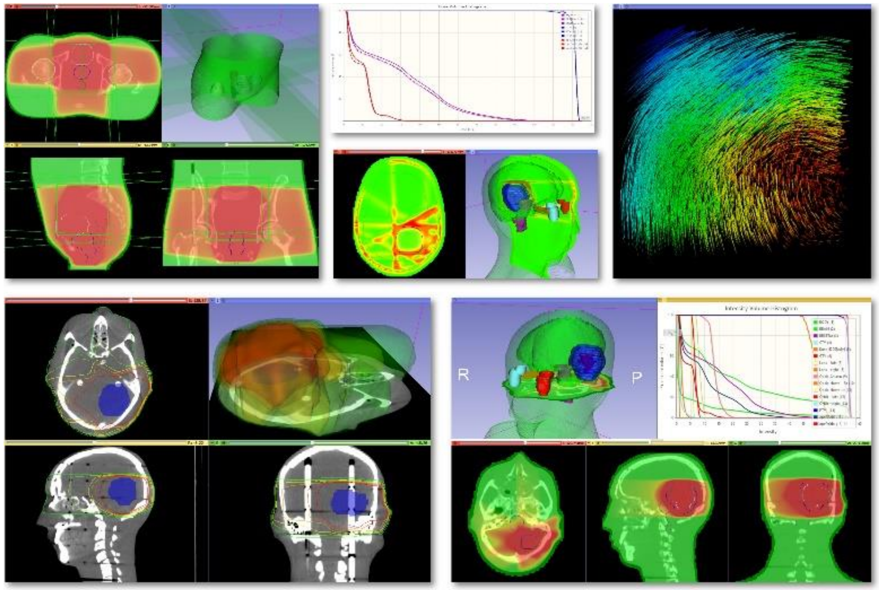
No coding

MeVislab (ITK GUI)
Slicer3D[1,2,4]
SMILI[2]
milxView (linux only)[2,3,4]
itkSNAP[1]

Elastix
Advanced Normalisation Tools (ANTS)

SimpleITK (Python, C#, Java, wrappers) [2,3,4]
ITK/VTK (C++/Python) [2,3,4]

Coding



Slicer3D SlicerRT plugin

[1] Useful to contour/insert landmark points
[2] Can read DICOM-RT structures from TPS
[3] GUI not supported
[4] 3D contour/distance metrics

SimpleITK (Python)

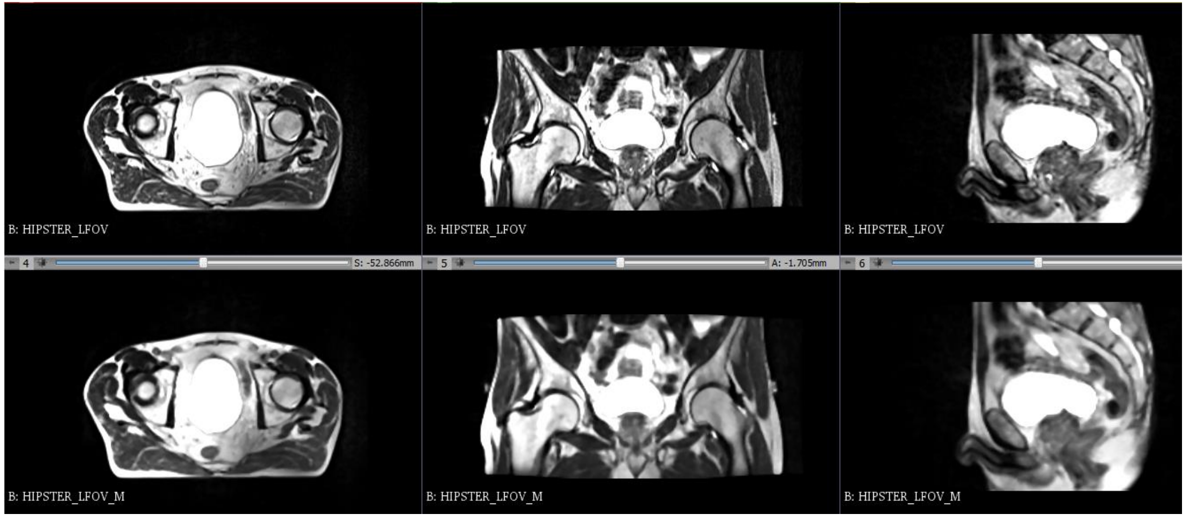
```python
import SimpleITK as sitk

reader = sitk.ImageFileReader()
reader.SetFileName ( 'HIPSTER_LFOV.nii.gz' )
image = reader.Execute()

filter = sitk.MedianImageFilter()
filter.SetRadius(1)
image = filter.Execute ( image )

writer = sitk.ImageFileWriter()
writer.SetFileName ( 'HIPSTER_LFOV_M.nii.gz' )
writer.Execute ( image )
```

http://www.simpleitk.org/



Original

Filtered

Conclusion

- Important to understand the components for best results
- Image quality important (~~6mm slices~~)
- Don’t trust the black box
- Registration transforms/deformations can be reused for other purposes
- Deep learning methods are coming…

Australia's
National Science
Agency

New Advances in Image Registration

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ACPSEM Medical Image Registration Special Interest Group
4th August 2020

The ACPSEM Medical Image Registration Special Interest Group (MIRSIG) Online Webinars

Questions and Answers from the August 2020 Webinar Chaired by Michael Jameson (Talk 1 by Jason Dowling)

Question 1: Which deep learning approach is better -supervised vs. unsupervised?

Answers:

This is an interesting question. Supervised methods (such as the paper by de Vos presented earlier) might have the best results now, however they need for a lot of training data (and a long time to train). Unsupervised training can be a faster and cheaper workaround and there are some promising methods with very good results.

Question 2: Failure modes for current DIR can be quite diverse. Do you think Deep Learning failure modes will be even more unpredictable?

Answers:

This is a very good point and there may be an impact on QA procedures. One of the advantages of traditional image registration models is that it's possible to check each step of the process work and find exactly how and why a registration failure has occurred. With deep learning it can be difficult to work out which aspects of the input data and architecture may have failed. There is a hot research field called explainable deep learning that is attempting to address these concerns. Another issue is that the deep learning may be trained to be more specialised to a specific task and might be less robust to cases outside the training set.