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CompBioMed

A Centre of Excellence in Computational Biomedicine

e-Seminar series

e-Seminar #20

Introduction to Biomedical Image Registration and the Parallel Framework for Image Registration

9 December 2021

The e-Seminar will start at 3pm CET / 2pm GMT

Presenter:

Daniele Tartarini

(The University of Sheffield)

Moderator:

Tim Weaving

(University College London)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 675451

INSILICO WORLD

https://insilicoworld.slack.com/archives/C0151M02TA4

The e-Seminar series is run in collaboration with: VPH Institute Building the Virtual Physiological Human

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Welcome!

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Outline

- Introduction to Image registration
- Quality measures/cost functions
- Introduction on pFIRE
    - Activity in Compbiomed
    - Refactoring and exascale
- Example of applications

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Image Acquisition Modalities

- CT – Computerised Tomography. Based on X-ray images
- PET/SPECT Single-Photon Emission Computed tomography. Uses gamma rays and requires radioactive tracer
- MNR/MRI- Magnetic Nuclear Resonance
- Ultrasound. High frequency sound waves

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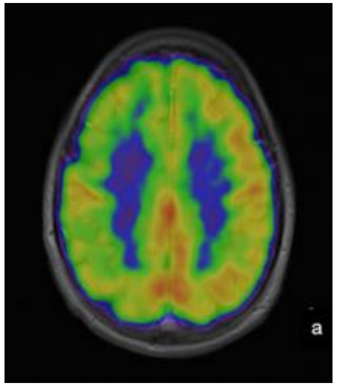
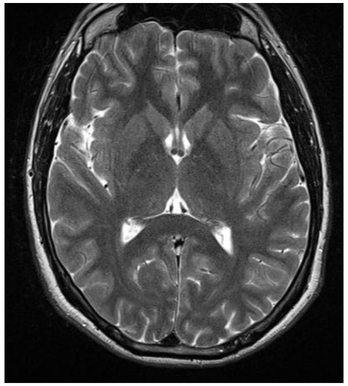
Multi Modality Registration

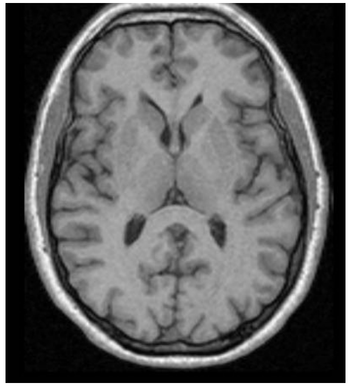
PET-MRI



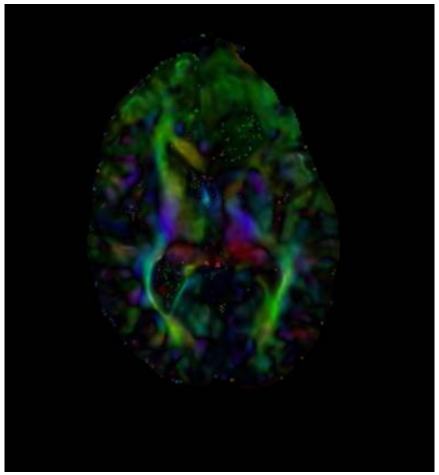
CT-MRI



MRI



Diffusion Tensor Imaging



Diffusion Weighted Imaging

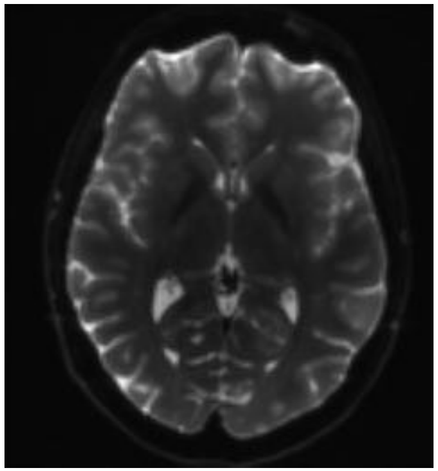


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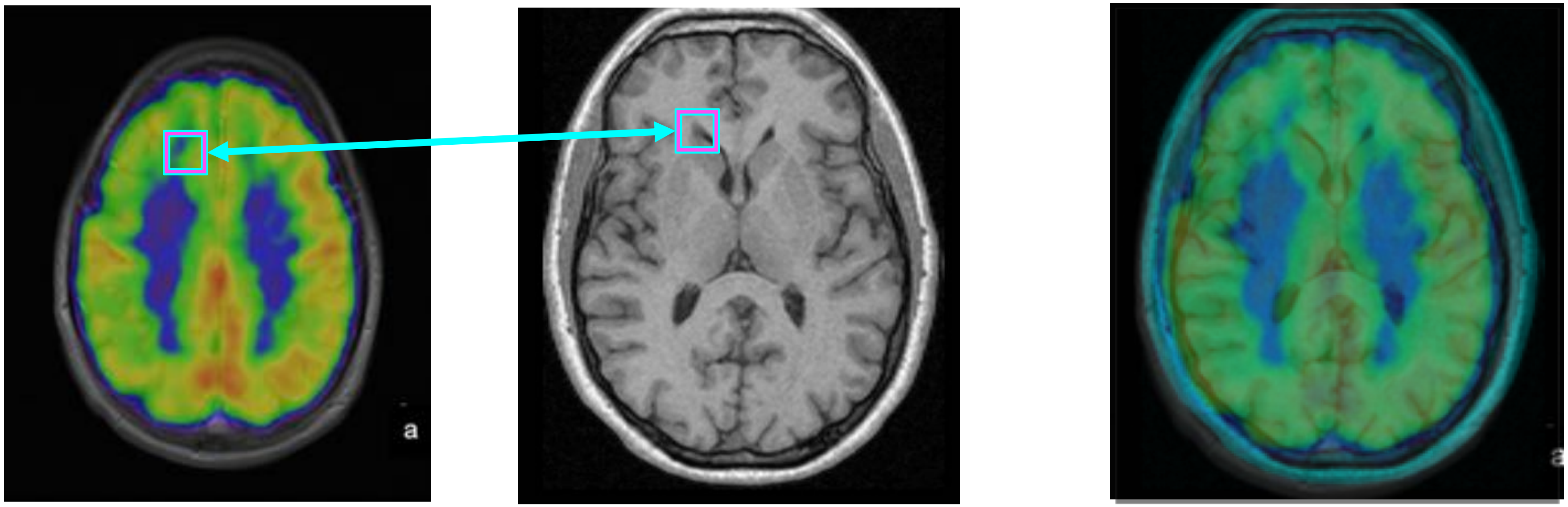
Image Registration

Multi modality image registration



PET CT

Need for Registration

- Multi modality registration (e.g. MRI-PET)
- Patient moving during session: CT/MRI scan
- Imaging of patients at different sessions
- Acquisition of time dependent series

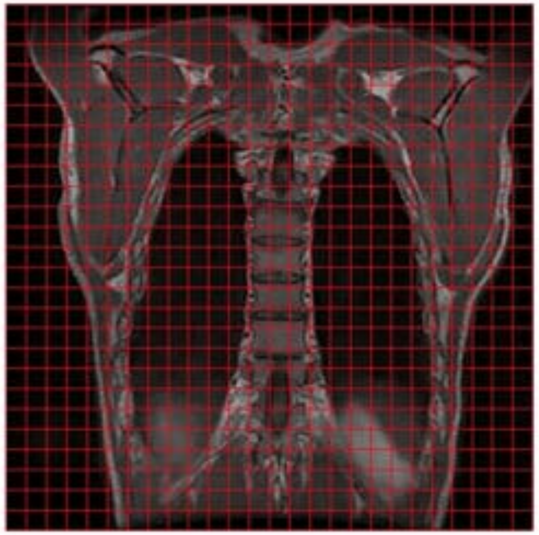
- Morphological chances due patient growth
- Deformations due to disease evolution (e.g.)
- Scanner calibration and geometrical distortion

- Superposition of biomechanical modelling meshes

Image Registration

An example: CT of thorax

Fixed image



Moved image

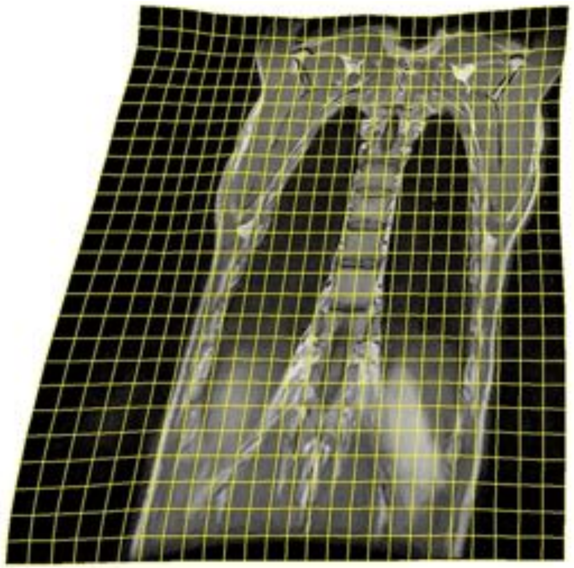
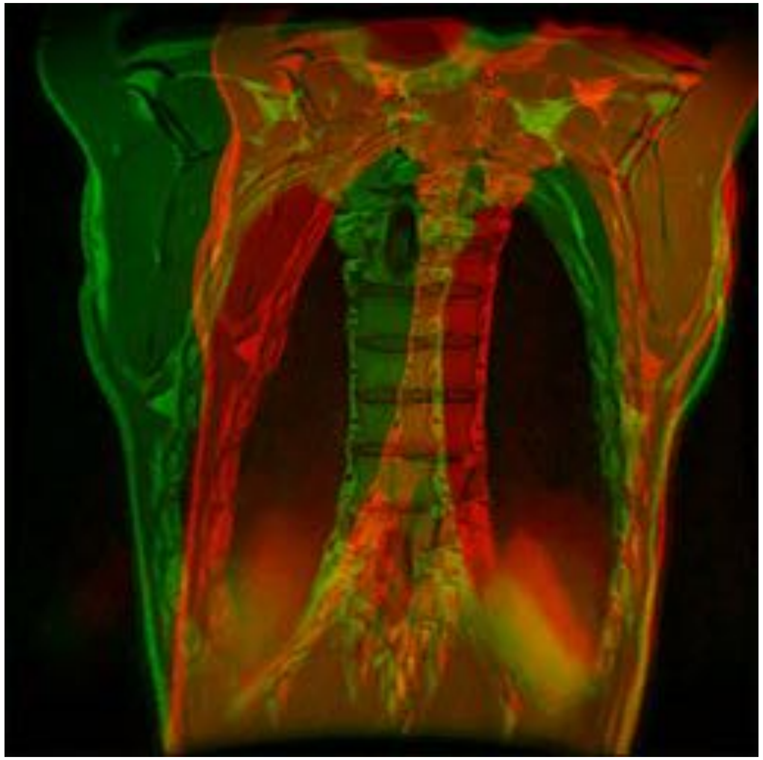


Image registration: finds the mathematical function that maps the moved image onto the reference image

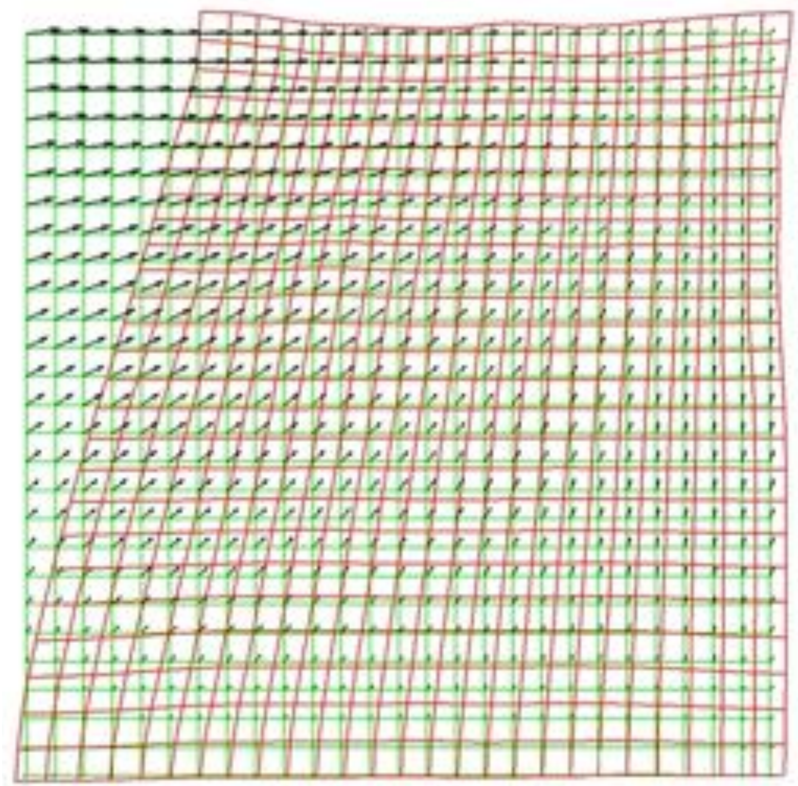
Image Registration

An example: CT of thorax

Overlap fixed/moved image in RGB channels



Registration Map



The mapping function can be represented as a field of vectors joining corresponding points.

Image Registration

The source (or moved) image ***m*** is registered to the target (or fixed) image ***f***.

We search for points in ***m*** which match points in ***f***.

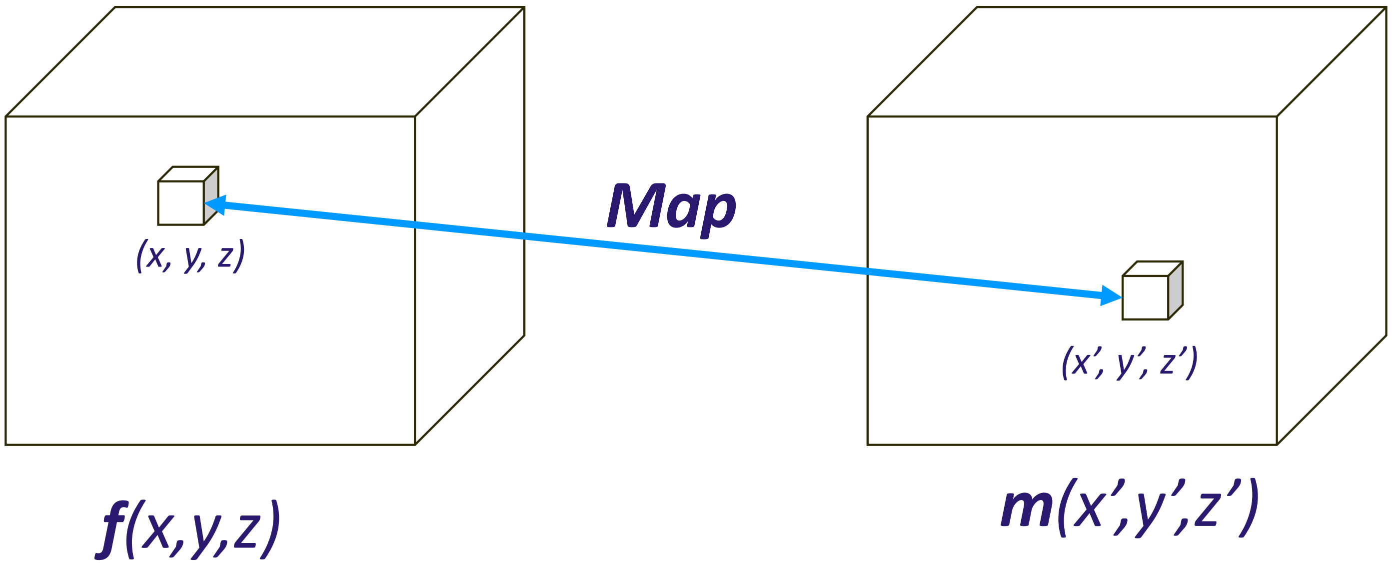


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Image Registration

- In 3D the mapping function can be expressed in the form of 3 functions.

$$x' = u(x, y, z) + x$$
$$y' = v(x, y, z) + y$$
$$z' = w(x, y, z) + z$$

  - The mapping is one-to-one.
  - *u, v, w* are displacement functions.

- For simplicity registration will be illustrated with 2D examples. Theory translates to 3D

Special mappings

- Translation

$$u = a_1$$
$$v = a_2$$

- Rigid rotation with translation

$$u = a_1 + x \cdot \cos(\theta) + y \cdot \sin(\theta)$$
$$v = a_2 - x \cdot \sin(\theta) + y \cdot \cos(\theta)$$

- Affine

$$u = a_{11} + a_{12} \cdot x + a_{13} \cdot y$$
$$v = a_{21} + a_{22} \cdot x + a_{23} \cdot y$$

Non-linear Mapping

- The mapping function is computed on a grid of points (nodes) spaced *D* pixels apart.
- Same approach as in FEM analysis
- The a_x a_y are the values of the mapping at the grid nodes.
- Values of the mapping between nodes are obtained by interpolation with local basis functions.

$$u = \sum_i a_{xi}\,\phi_i(x,y)$$

$$v = \sum_i a_{yi}\,\phi_i(x,y)$$

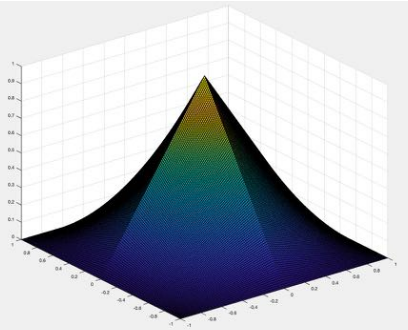

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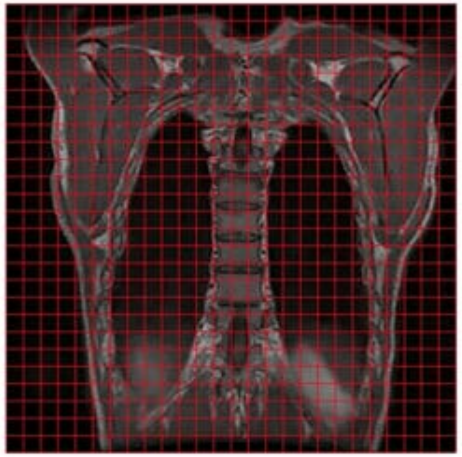
Image Registration

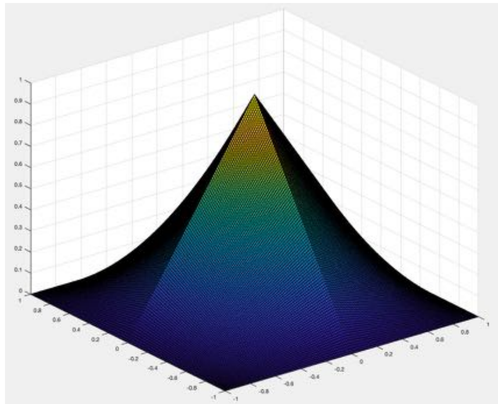
- An example of a local basis function is the bi/tri-linear interpolation function.

$$\phi_i(x,y) = (1-\left|\frac{x-x_i}{D}\right|)(1-\left|\frac{y-y_i}{D}\right|) \qquad \left\{-1 <= (\frac{x-x_i}{D}, \frac{y-y_i}{D}) <= 1\right\}$$

but other functions may be used (e.g. cubic, hermite ...)

- Each of these functions is centred on each node of the grid, co-ordinates x_i, y_i.
- Partition of unity holds





The Mapping Function

Assuming image intensities are the same at corresponding points

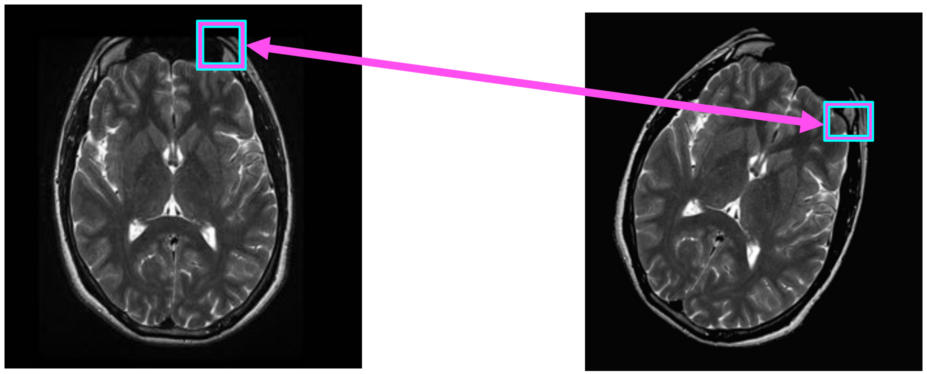
$$x' = u(x,y) + x$$
$$y' = v(x,y) + y$$

u and v are functions of coordinates

The mapping function is

$$f(x,y) = m(x,' y') = m(\, u(x,y) + x, v(x,y) + y)$$

$f(x,y)$ $m(x,' y')$



The Registration Equation

Using the Taylor series expansion and rearranging the terms:

$$f(x,y) = \mathrm{m}(x,y) + u(x,y)\left(\frac{\partial m\,(x,y)}{\partial x}\right) + v(x,y)\left(\frac{\partial m\,(x,y)}{\partial y}\right) + \ldots$$

The registration equation becomes:

$$f(x,y) - \mathrm{m}(x,y) = \frac{1}{2}\left[u(x,y)\left(\frac{\partial f(x,y)}{\partial x} + \frac{\partial m\,(x,y)}{\partial x}\right) + v(x,y)\left(\frac{\partial f(x,y)}{\partial y} + \frac{\partial m\,(x,y)}{\partial y}\right)\right] + \ldots$$

Note that the images become independent from u, v
Simplifying calculations

D.C. Barber et al. / Medical Image Analysis 11 (2007)

The Registration Equation

Higher order terms are truncated so it is accurate only for small values of u, v.

Expanding the basis functions:

$$u = \sum_i a_{xi}\,\phi_i(x,y) \qquad\qquad v = \sum_i a_{yi}\,\phi_i(x,y)$$

$$f(x,y) - \mathrm{m}(x,y) = \frac{1}{2}\left[\sum\nolimits_i a_{xi}\,\phi_i(x,y)\left(\frac{\partial f}{\partial x} + \frac{\partial m}{\partial x}\right) + \sum\nolimits_i a_{yi}\,\phi_i(x,y)\left(\frac{\partial f}{\partial y} + \frac{\partial m}{\partial y}\right)\right] + \ldots$$

The equation is linear in coefficients a_{ij}

One equations per voxel

D.C. Barber et al. / Medical Image Analysis 11 (2007)

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Finding Displacements Map

Organizing the equation in Matrix form

$$\boldsymbol{f} - \boldsymbol{m} = \boldsymbol{T}\boldsymbol{a}$$

The equation is usually overdetermined

- $\boldsymbol{f}, \boldsymbol{m}$ are vectors of size N
- $\boldsymbol{T}$ is a matrix of N*2P elements
- $\boldsymbol{a}$ is a vector of size 2P

$$\boldsymbol{a} = (\boldsymbol{T}^t\boldsymbol{T})^{-1}\,\boldsymbol{T}^t(\boldsymbol{f} - \boldsymbol{m})$$

Solution issues

The problem is ill-posed and ill-conditioned because the matrix

$$(\boldsymbol{T}^t\boldsymbol{T}) \quad \textit{in the equation} \quad \boldsymbol{a} = (\boldsymbol{T}^t\boldsymbol{T})^{-1}\,\boldsymbol{T}^t(\boldsymbol{f}-\boldsymbol{m})$$

The solution is very sensitive to noise and a constraint is required.

A suitable constraint is imposing smoothness via Laplacian:

$$\nabla^2 u(x,y), \nabla^2 v(x,y) = \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}, \frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2}$$

In discrete form the constraint is $\boldsymbol{La} = 0$

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Iterative Solution

$$\begin{bmatrix} \boldsymbol{f} - \boldsymbol{m} \\ 0 \end{bmatrix} = \begin{bmatrix} \boldsymbol{T} \\ \lambda \boldsymbol{L} \end{bmatrix} a$$

The solution is

$$\boldsymbol{a} = (\boldsymbol{T}^t\boldsymbol{T} + \lambda^2\boldsymbol{L}^t\boldsymbol{L})^{-1}\,\boldsymbol{T}^t(\boldsymbol{f} - \boldsymbol{m})$$

It derived form Taylor expansion so is accurate only for small displacements.
An Iterative procedure is required.

$$\boldsymbol{a}_0 = (\boldsymbol{T}^t\boldsymbol{T} + \lambda^2\boldsymbol{L}^t\boldsymbol{L})^{-1}\,\boldsymbol{T}^t(\boldsymbol{f} - \boldsymbol{m})$$
$$\boldsymbol{a}_1 = (\boldsymbol{T}^t\boldsymbol{T} + \lambda^2\boldsymbol{L}^t\boldsymbol{L})^{-1}\,\boldsymbol{T}^t(\boldsymbol{f} - \boldsymbol{m}(\boldsymbol{a}_0))$$
$$\boldsymbol{a}_2 = \ldots.$$

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Quality measures/Cost functions

Cost functions measure the registration quality

- Sum of Squares differences for images based on intensity

$$Q = \sum_{voxels} (\boldsymbol{f} - \boldsymbol{m}(\boldsymbol{a}))^2$$

- Mutual information

$$MI(A,B) = \sum_{a,b} p_{AB}(a,b) \cdot \frac{\log(p_{AB}(a,b))}{p_A(a) \cdot p_B(b)}$$

is currently considered a gold standard measure of image similarity.

(Studholme, et al, 1995) and (Collignon, ed al. 1995) in Information Proc Med Imaging

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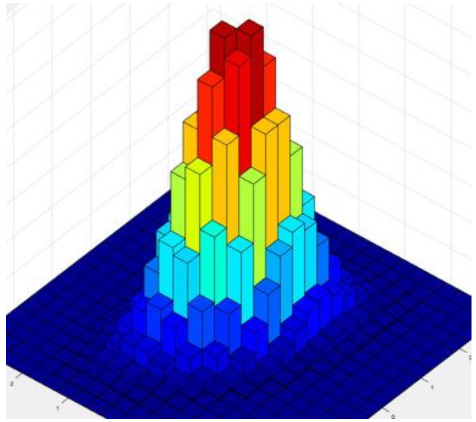
Sum of Squares

The Sum of Squared differences criterion is computationally efficient but it is sensitive intensity difference.



An intensity image can be converted to a binary image augmenting dimensionality:

$$\boldsymbol{f}(x,y) \dashrightarrow \boldsymbol{f}_{\mathrm{b}}(x,y,s)$$

Mapping between binary images is not unique and need extra constraints are needed (e.g. smoothness)

$$f_{\mathrm{b}}(x,y) = \mathrm{m_b}(\mathrm{x}+u,\mathrm{y}+v)$$

$$f_{\mathrm{b}}(x,y) - \mathrm{m_b}(\mathrm{x}+u,\mathrm{y}+v) = \frac{1}{2}\left[u(x,y)\left(\frac{\partial \boldsymbol{f}_b(x,y)}{\partial x} + \frac{\partial \boldsymbol{m}_b(x,y)}{\partial x}\right) + v(x,y)\left(\frac{\partial \boldsymbol{f}_b(x,y)}{\partial y} + \frac{\partial m_b(x,y)}{\partial y}\right)\right] + \ldots$$

(Barber DC, Hose R, J. Med. Eng & tech., 2005)

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Mutual Information

The Mutual information MI(A,B) measures the independence of images A and B as the distance between the joint distribution $p_{AB}(a,b)$ and the distribution associated to the case of independent images (Kullbacl-Leibler measure).

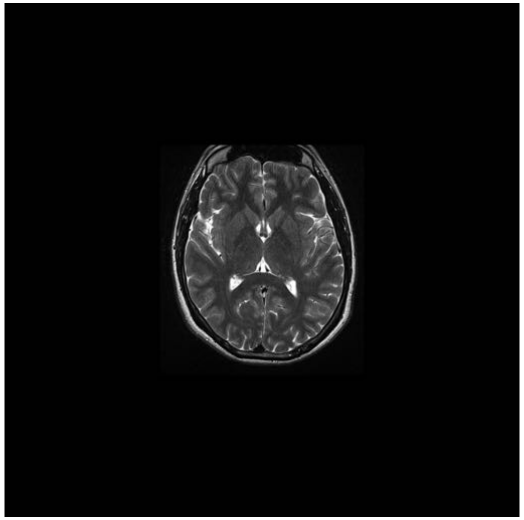
$$MI(A,B) = \sum_{a,b} p_{AB}(a,b) \cdot \frac{\log(p_{AB}(a,b))}{p_A(a) \cdot p_B(b)}$$

The MI of the image intensity values of corresponding voxel pairs in mapping is maximal if the images are geometrically aligned.
Because no assumptions are made regarding the nature of the relation between the image intensities, this criterion is very general and powerful and can be applied automatically on multi-modality images.

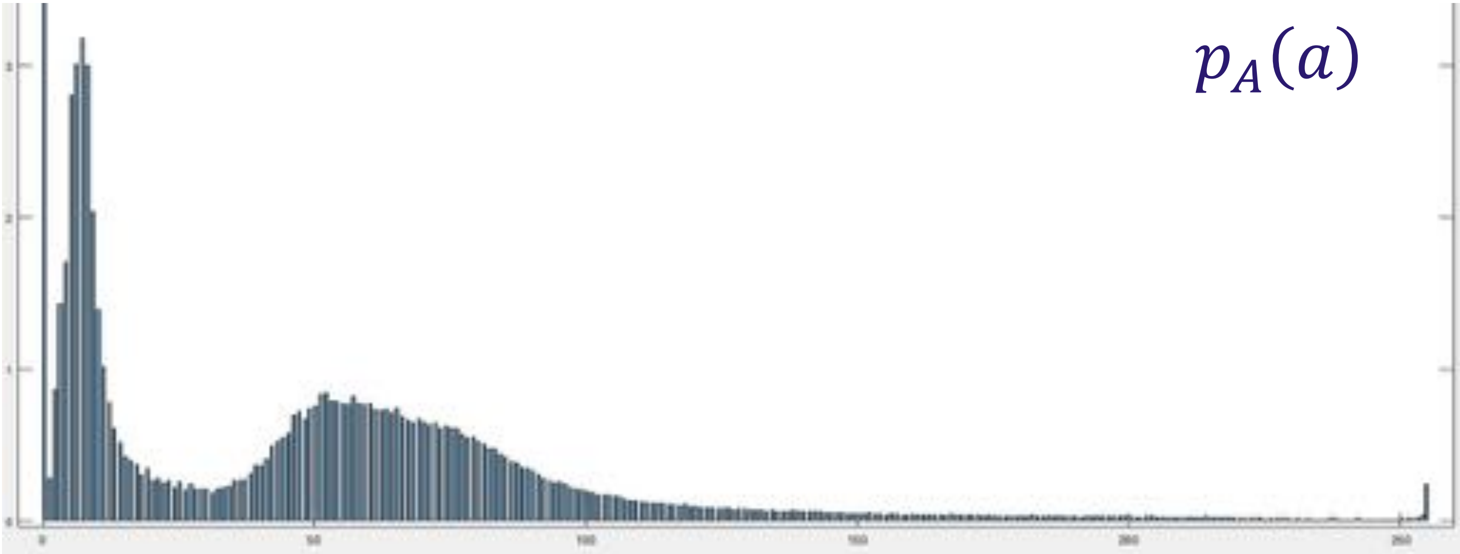
Considered the golden standard.
Computationally expensive.

(Maes, IEEE proc 2013)

Histogram



$p_A(a)$

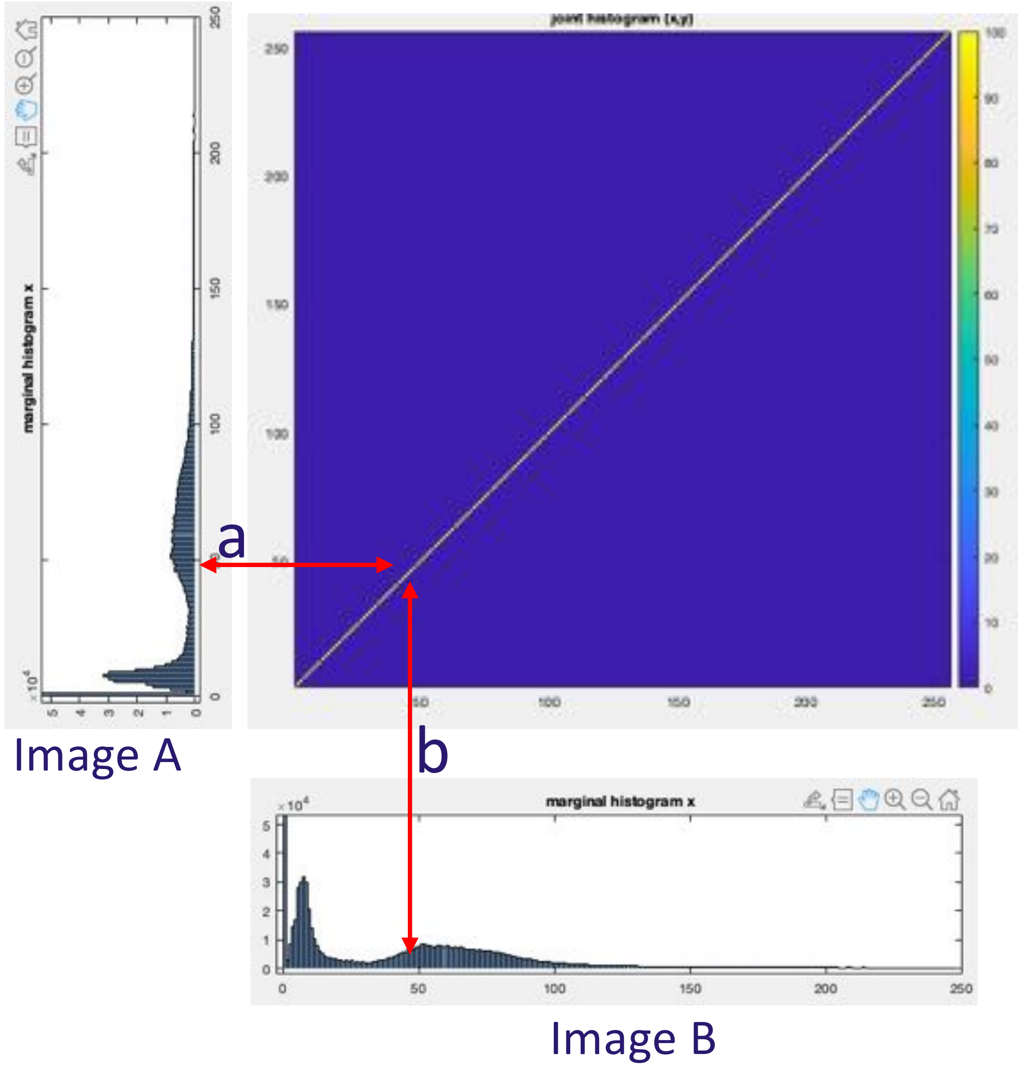


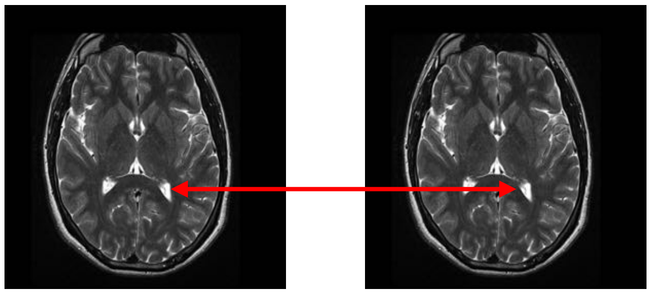
Joint Histogram

The Joint histogram of a perfectly registered image is concentrated on a line

$$h(a, b)$$

is the number of pixels having grey value a in image A and b in image B





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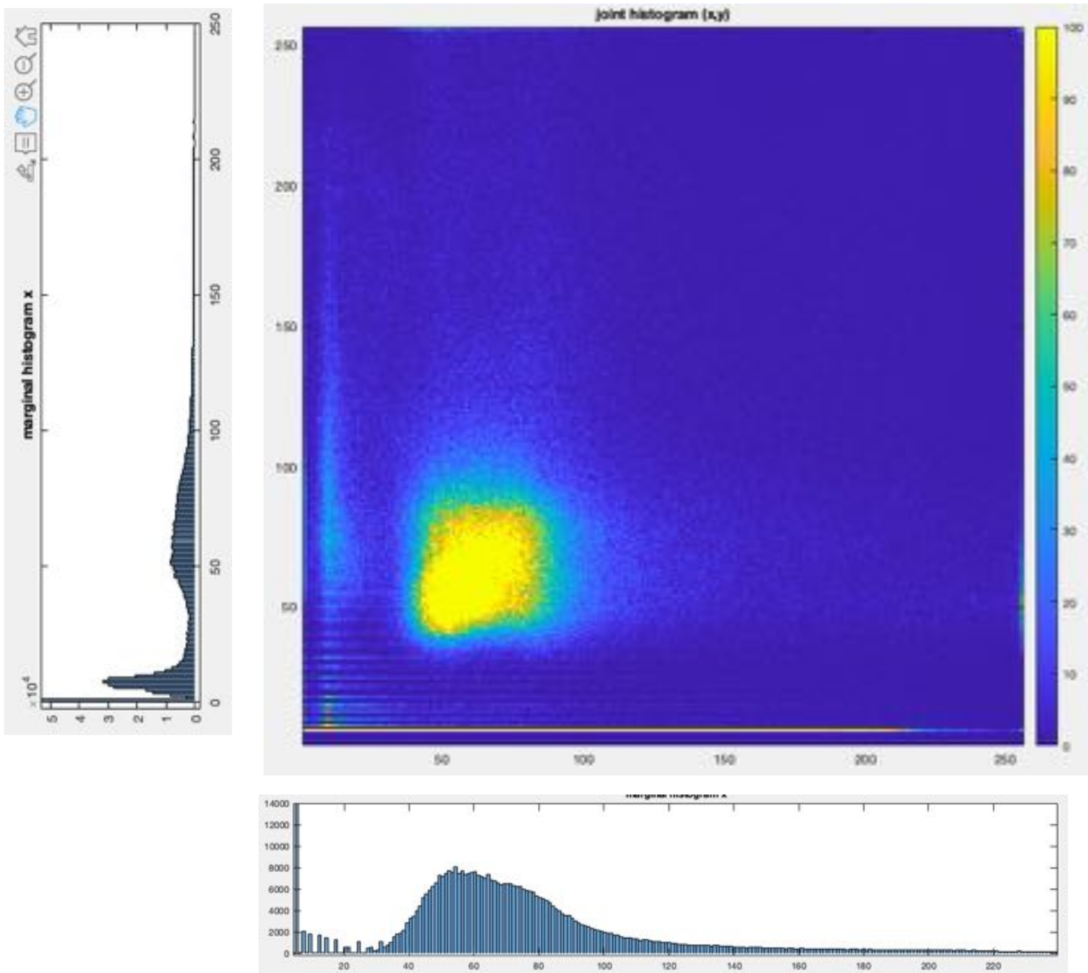
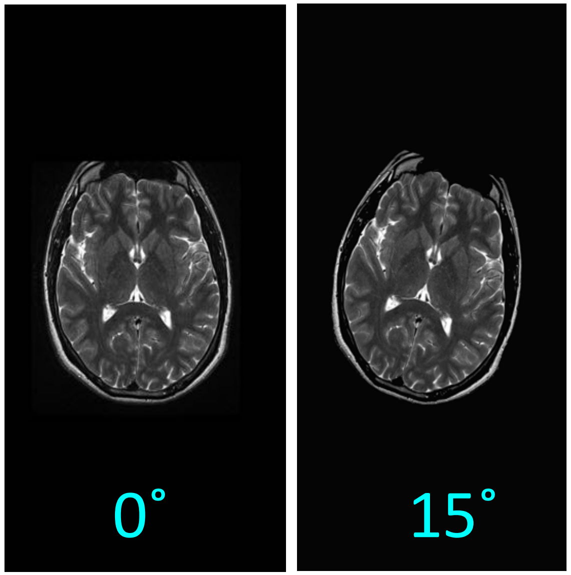
Joint Histogram

In this case image B is rotated of 15˚
The histogram pattern is dispersed (entropy)





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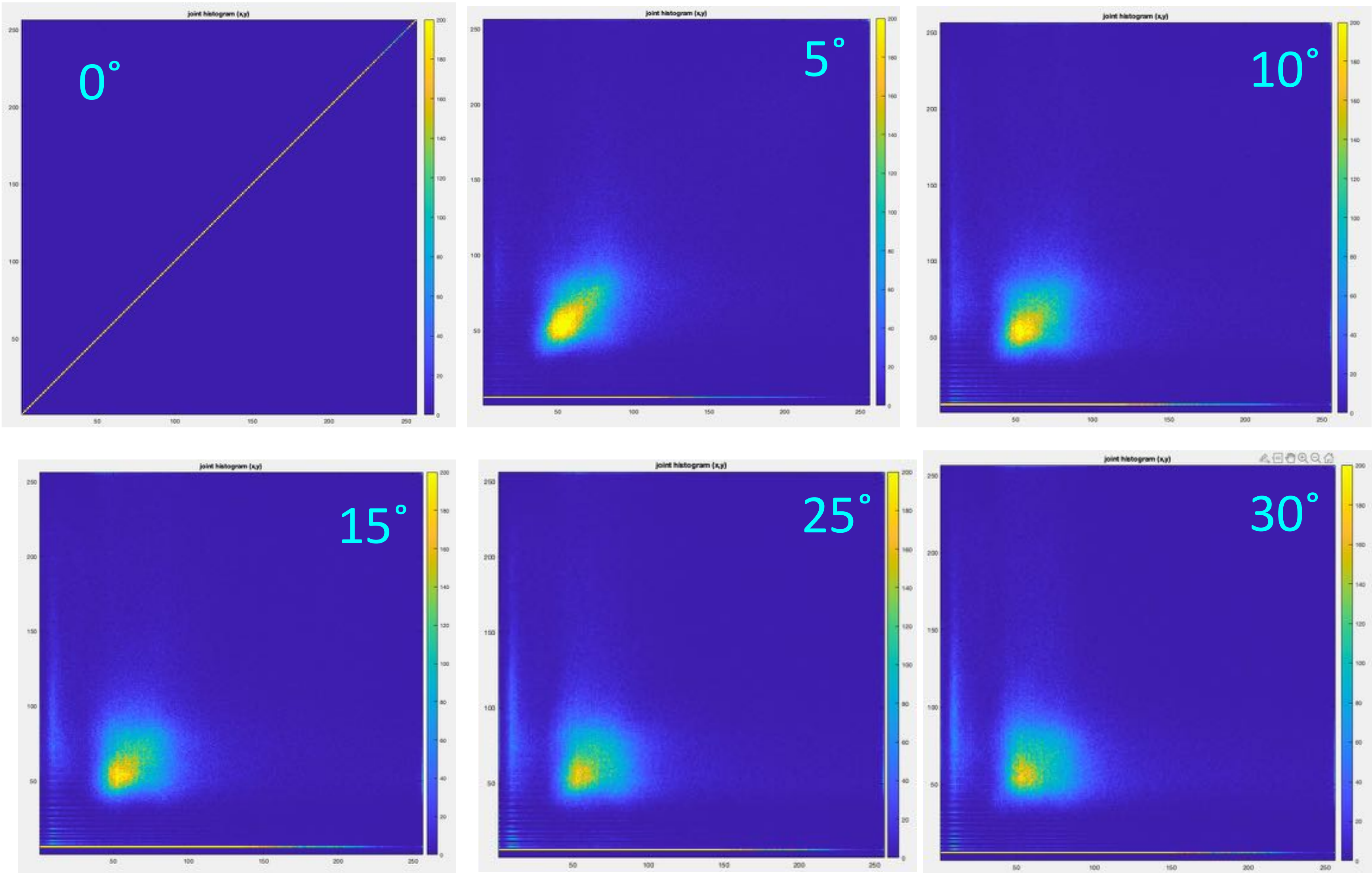
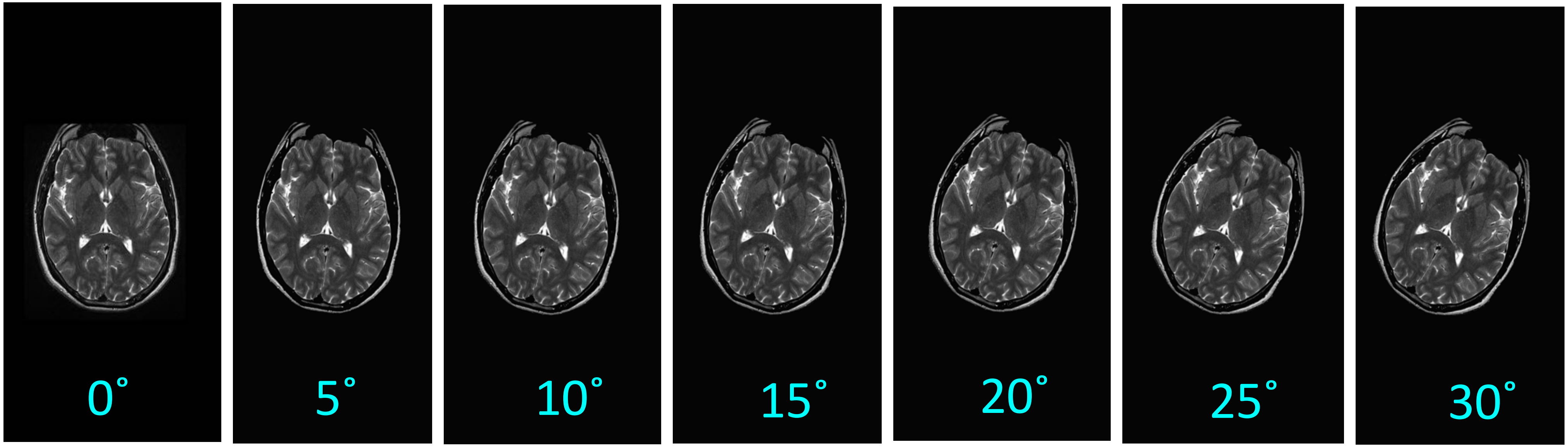
Joint Histogram

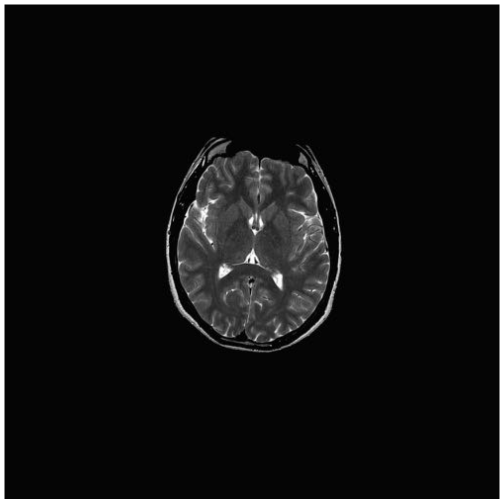
Entropy increases with rotation

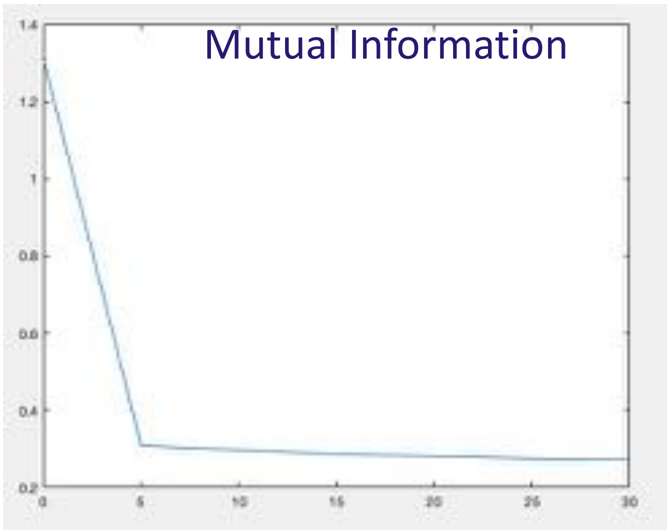


Mutual Information

Rotations







[1.3104, 0.3076, 0.2977,0.2864, 0.2808, 0.2757, 0.2737];

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pFIRE: Parallel Framework for Image REgistration

Derived by published work of RD Hose and D Barber

Iterative registration algorithm

Implements Mutual Information

Size of mesh D is initially image_dimension/4; iteration is repeated halving it and until mutual information does not decrease

Stopping criterion when displacements at iteration << voxel size
Computation of lambda depends on MI

Solver Krylov subspace implemented by PETSc
Parallel MPI implementation for HPC
Optimisations are implemented accounting for matrix sparsity and efficient of MPI distribution of computation

(Barber DC, Hose R, J. Med. Eng & tech., 2005)

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Application Incubation Program

Registration Enhancement

Optimise registration algorithm
Validation and feedback from users

Fast Track

Software Quality Assurance (ISO/IEC 25000, SQuaRE)
FAIR-SW (Findable, Accessible, Interoperable and Reusable)
Reproducibility
Reliability

Deep Track

Optimisation and Parallelisation
Cloud-HPC/HPC Deployment
Preparing for Exascale HPC (10^{16} FLOPS)

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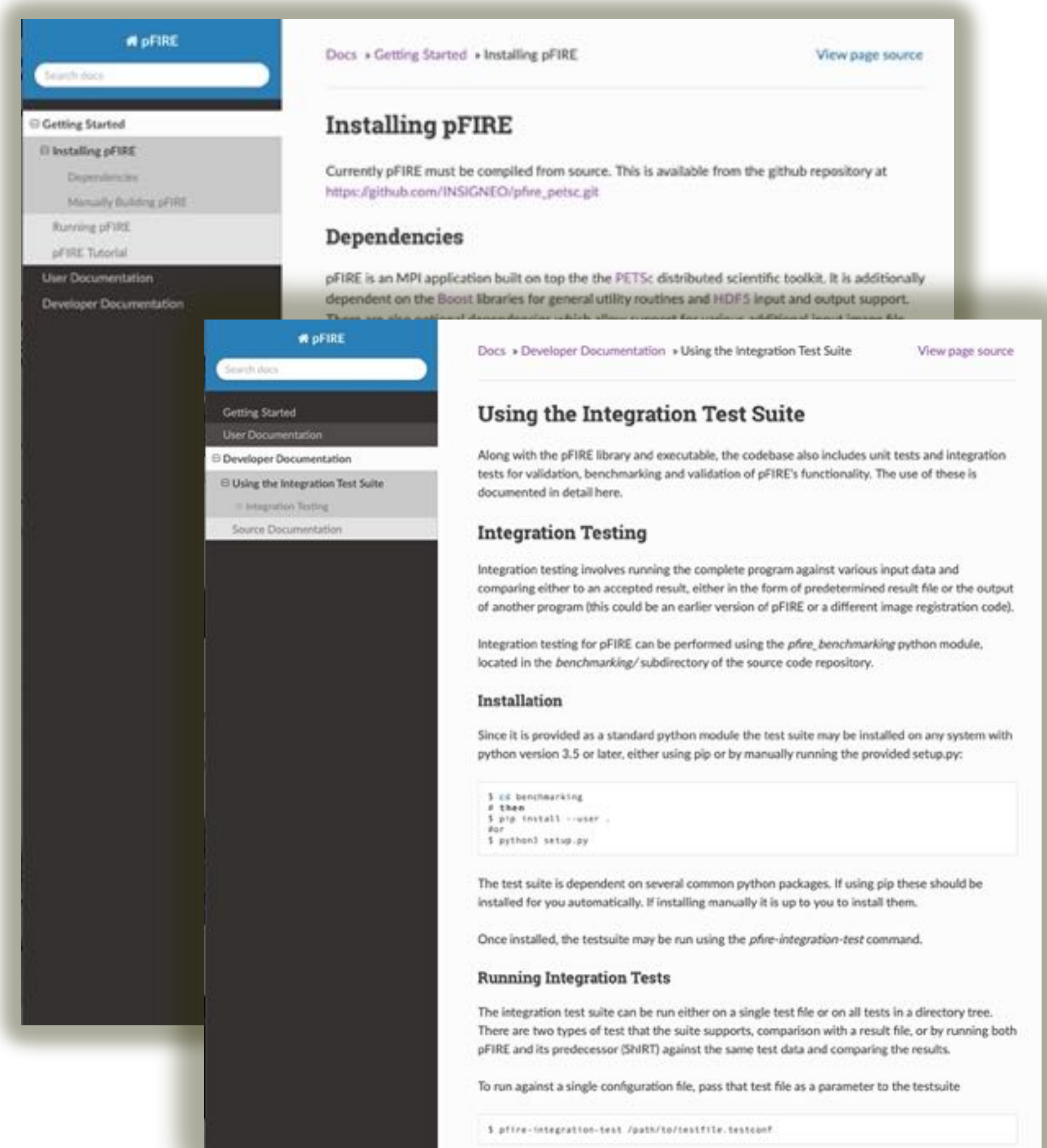
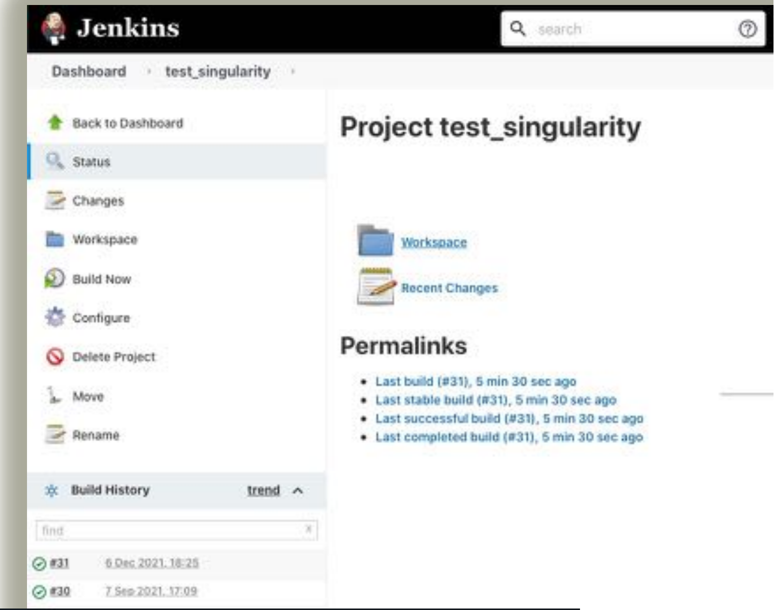
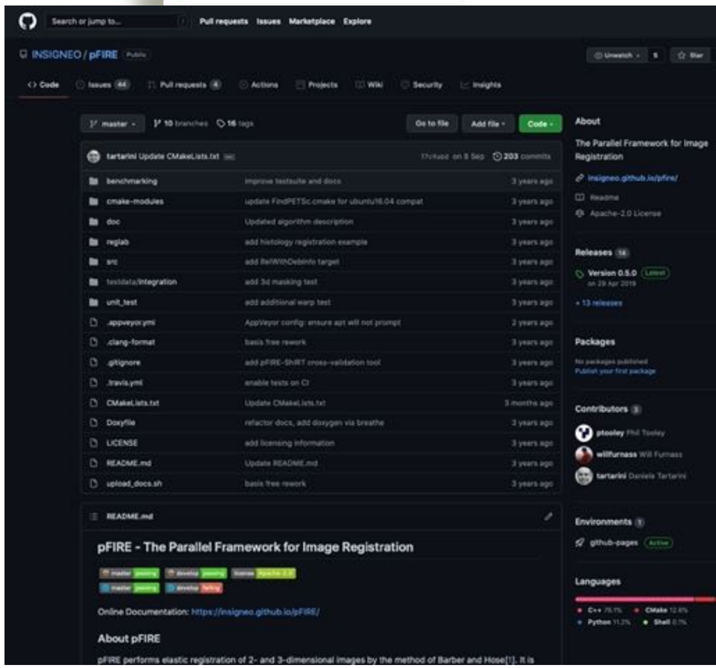
pFIRE







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FAIR-SW and best practices

Findable, Accessible, Interoperable, Reproducible Software principles

Concurrent versioning system: http://github.com/INSIGNEO/pFIRE

Continuous Integration and deployment: TravisCI → Jenkins (MPI)

Documentation as code: ReadTheDocs Documentation + UML

Distributed as Source code, Docker and Singularity images

hub.docker.com/r/insigneopfire/pfire

Standard Data Formats: HDF5, DICOM, png, tiff (replaces proprietary format)

(FAIR SW Research Data alliance 2021)

C++ Dependencies complexity

Spack package manager

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Containerization experience

Docker: Ideal for workstation. Introduced the rootless mode for MPI

Singularity better support for MPI but need to run compatible MPI implementations between container and host

pFIRE Container Architecture

pFIRE (Singularity)

Library dependencies Layer (Singularity)

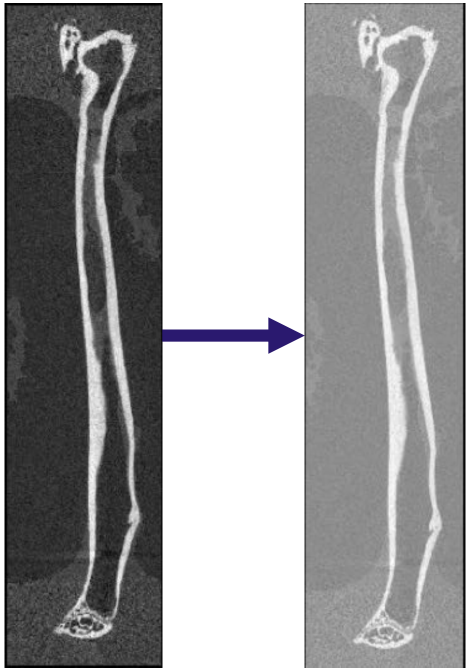
OS Layer (Docker)

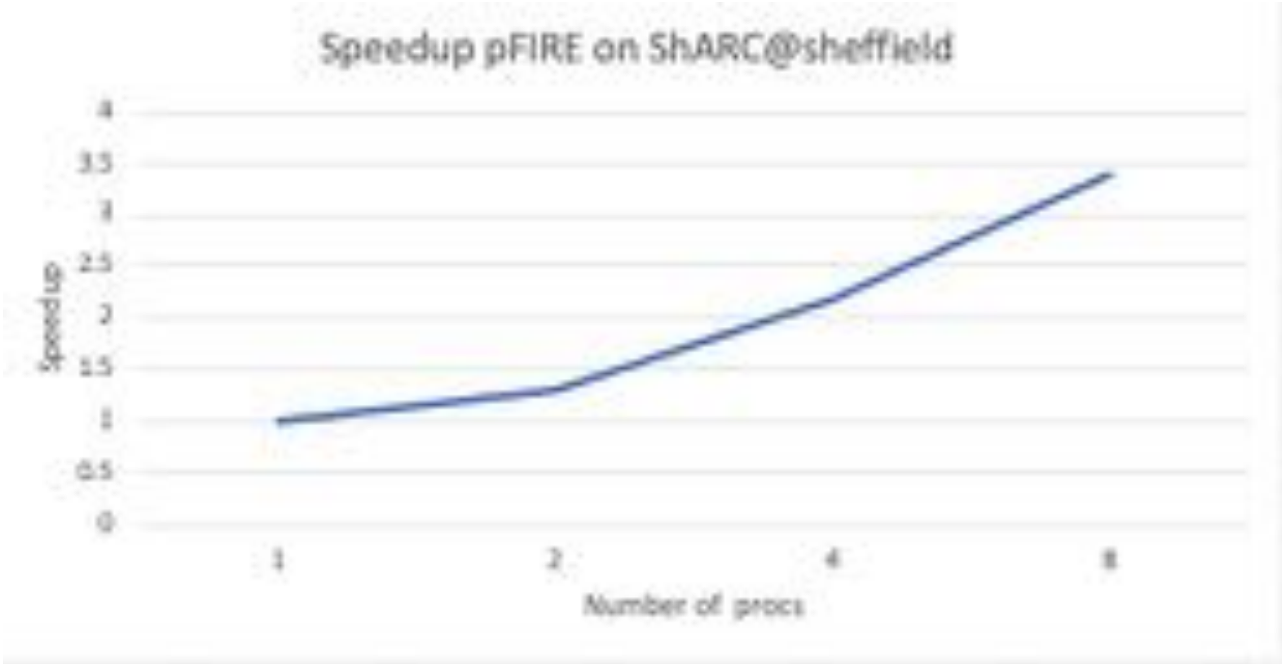
Evolving technology with limitations

Restrictions on the filesystem and user permissions
Singularity MPI hybrid needs tweaks for performance

Computational Performance

3D CT Tibia





ShArC node specifications:

CPUs: 2 x Intel Xeon E5-2630 v3@2.4GHz

RAM: 64 GiB (4 GiB / core)

Hyperthreading disabled

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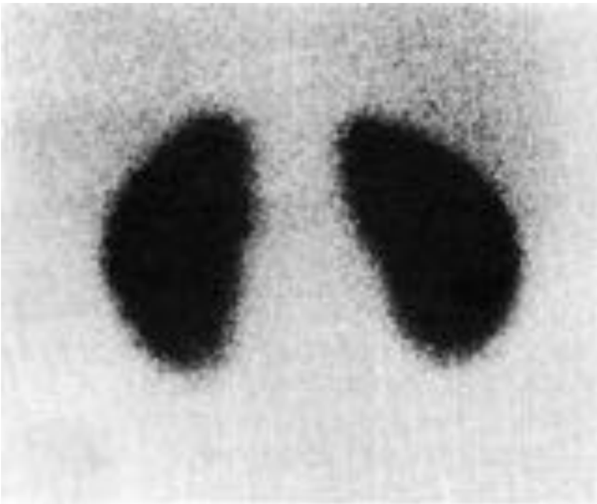
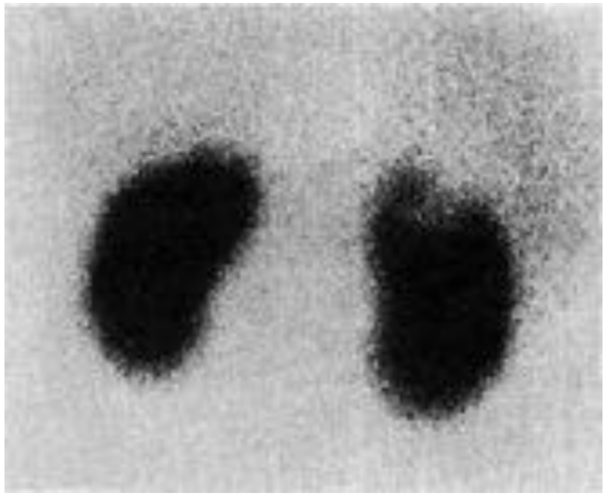
Segmentation via registration

Reference image



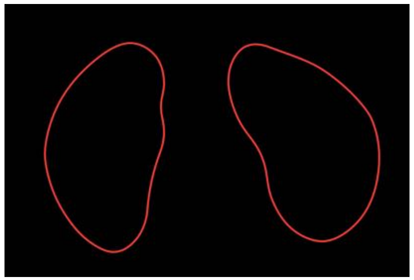
Registration

Patient image



Automatic segmentation

Reference Kidney segmentation



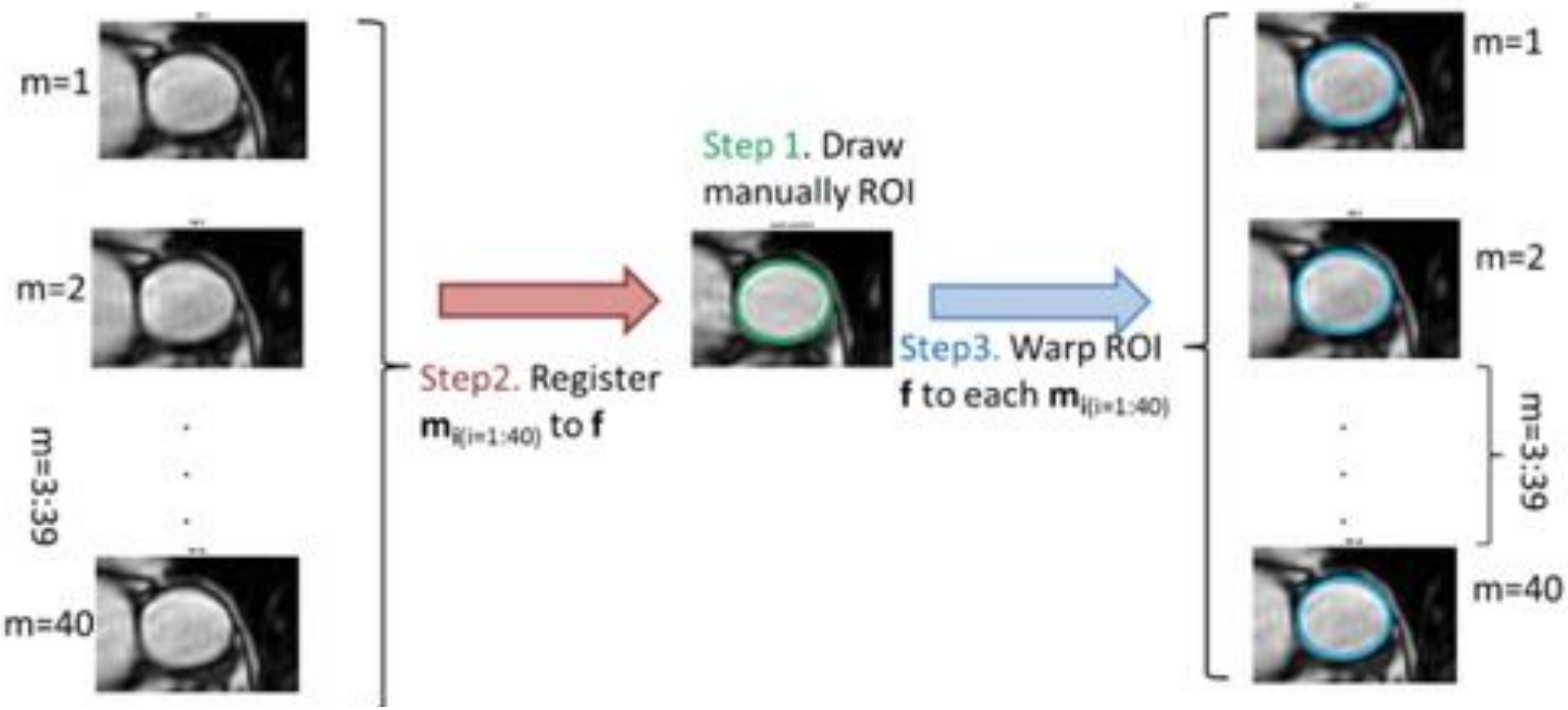
Map contour

Creative license SPECT and manual segmentation

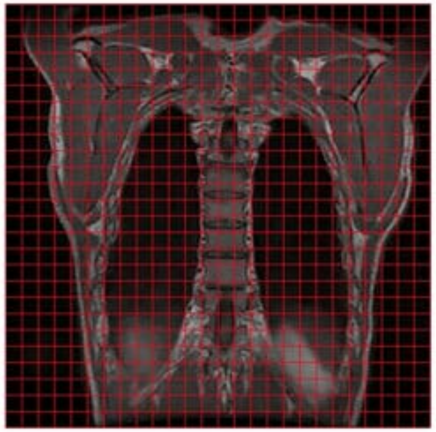
Methodology in Barber, D. C. 2005)

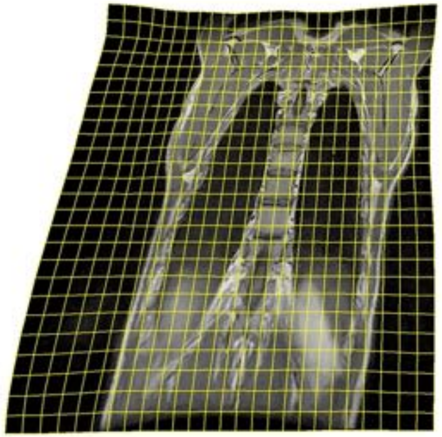
Registration Based Segmentation

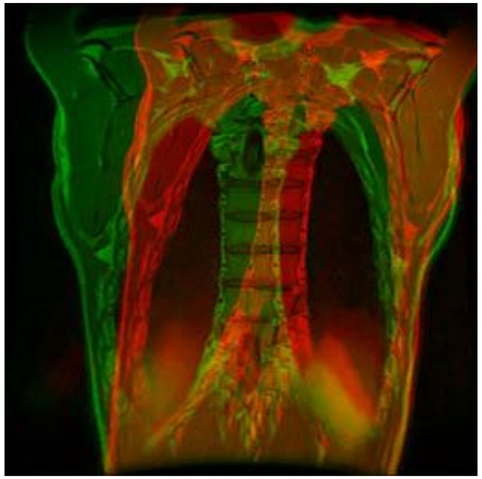
Systolic flow Vessel ROI

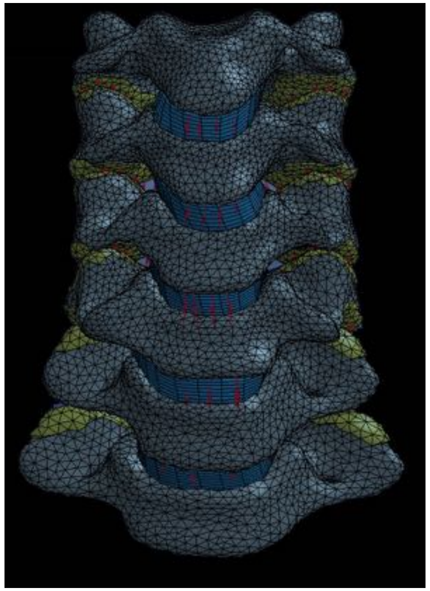


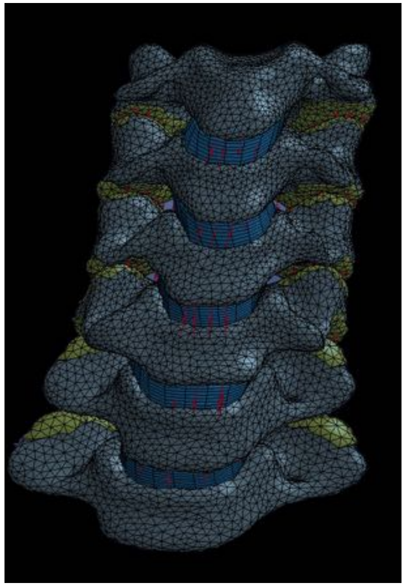
Spine Meshing











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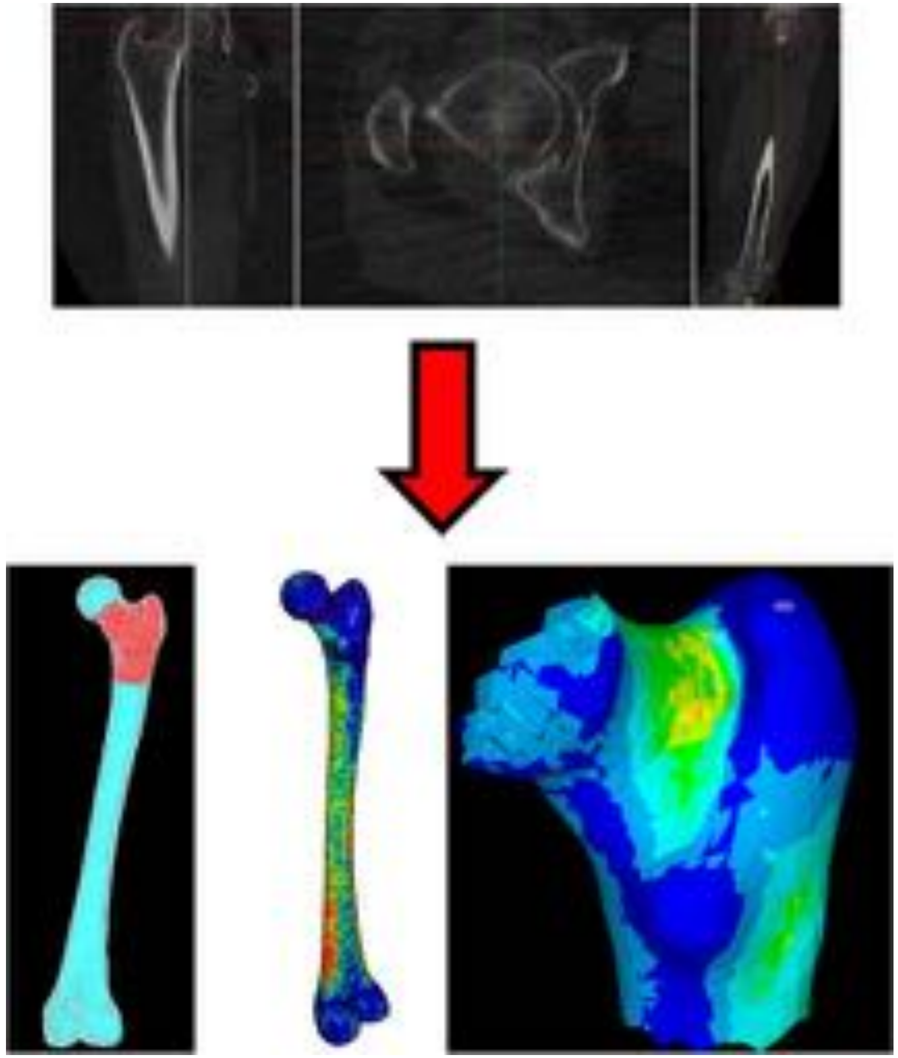
CT2S pipeline including image registration

The CT2S service provides an estimate of the strength of human bone, using non-invasive medical imaging



Source https://ct2s.insigneo.org/ct2s/

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Q&A

To pose a question, you can write your question
in the “Questions” tab

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 675451

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