Imperial College London

Machine Learning for Imaging
Image Registration

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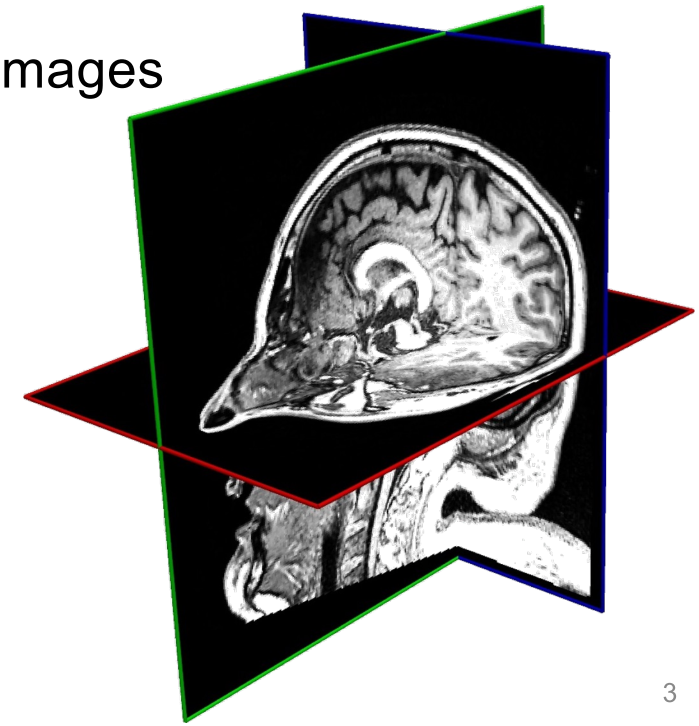
Overview

- Introduction to image registration
- Coordinate systems and transformations
- Intensity-based image registration
- Neural networks for image registration

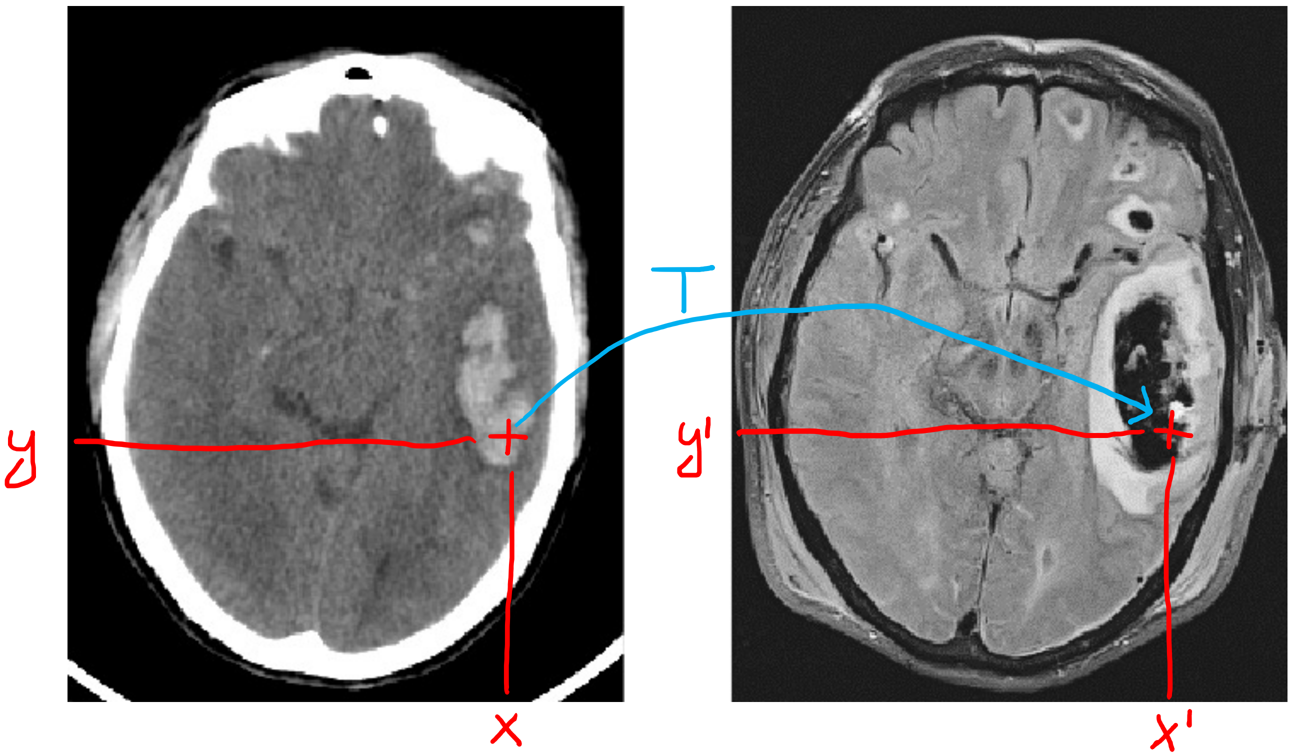
Images

- d-dimensional arrays with scalar/vector values
- Mathematical functions: $f: \mathbb{R}^d \to \mathbb{R}^n$
  - Often, we have three-dimensional, scalar-valued images $d = 3, n = 1,\ f(x, y, z) \in \mathbb{R}$
- Meta information
  - Scale: element spacing (e.g. in mm)
  - Orientation: directions of main axes
  - Position: image origin



Medical Image Registration

Establish spatial correspondences between images

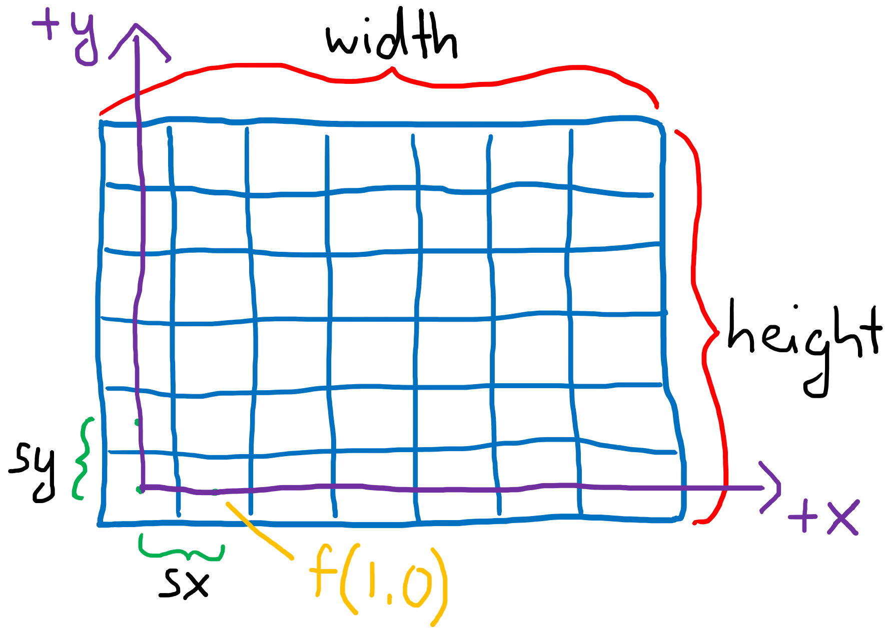


$$\begin{pmatrix} x' \\ y' \end{pmatrix} = T \begin{pmatrix} x \\ y \end{pmatrix}$$

Coordinate Systems

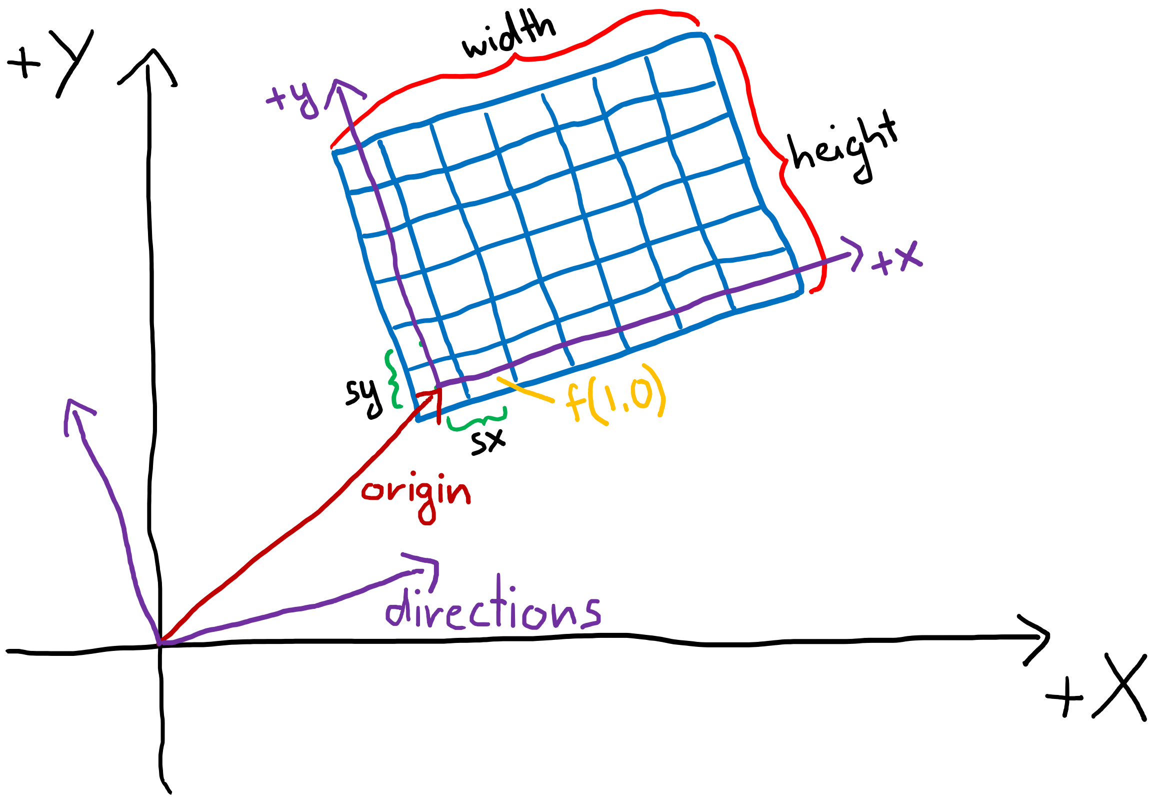
Coordinate Systems

Image coordinate system



Coordinate Systems

World coordinate system



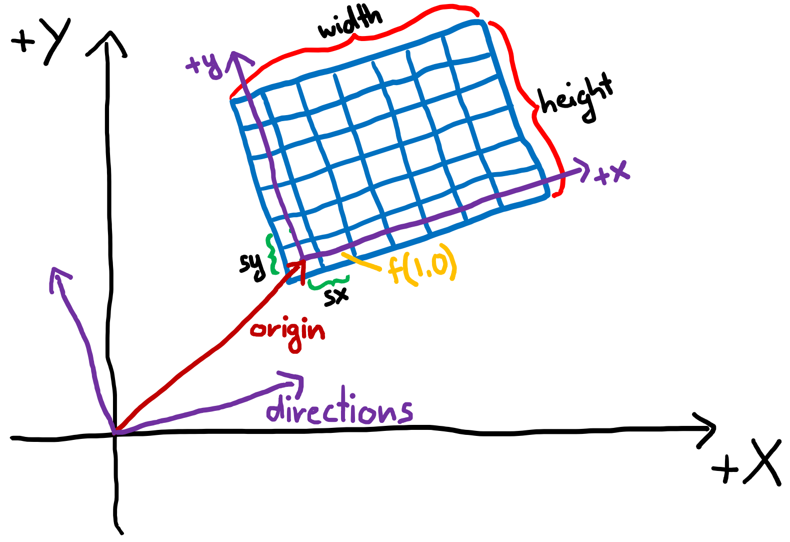
Coordinate Systems

Image to world

$$\begin{pmatrix} X \\ Y \\ 1 \end{pmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & ox \\ 0 & 1 & oy \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} dxx & dyx & 0 \\ dxy & dyy & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} sx & 0 & 0 \\ 0 & sy & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{T_{ItW}} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

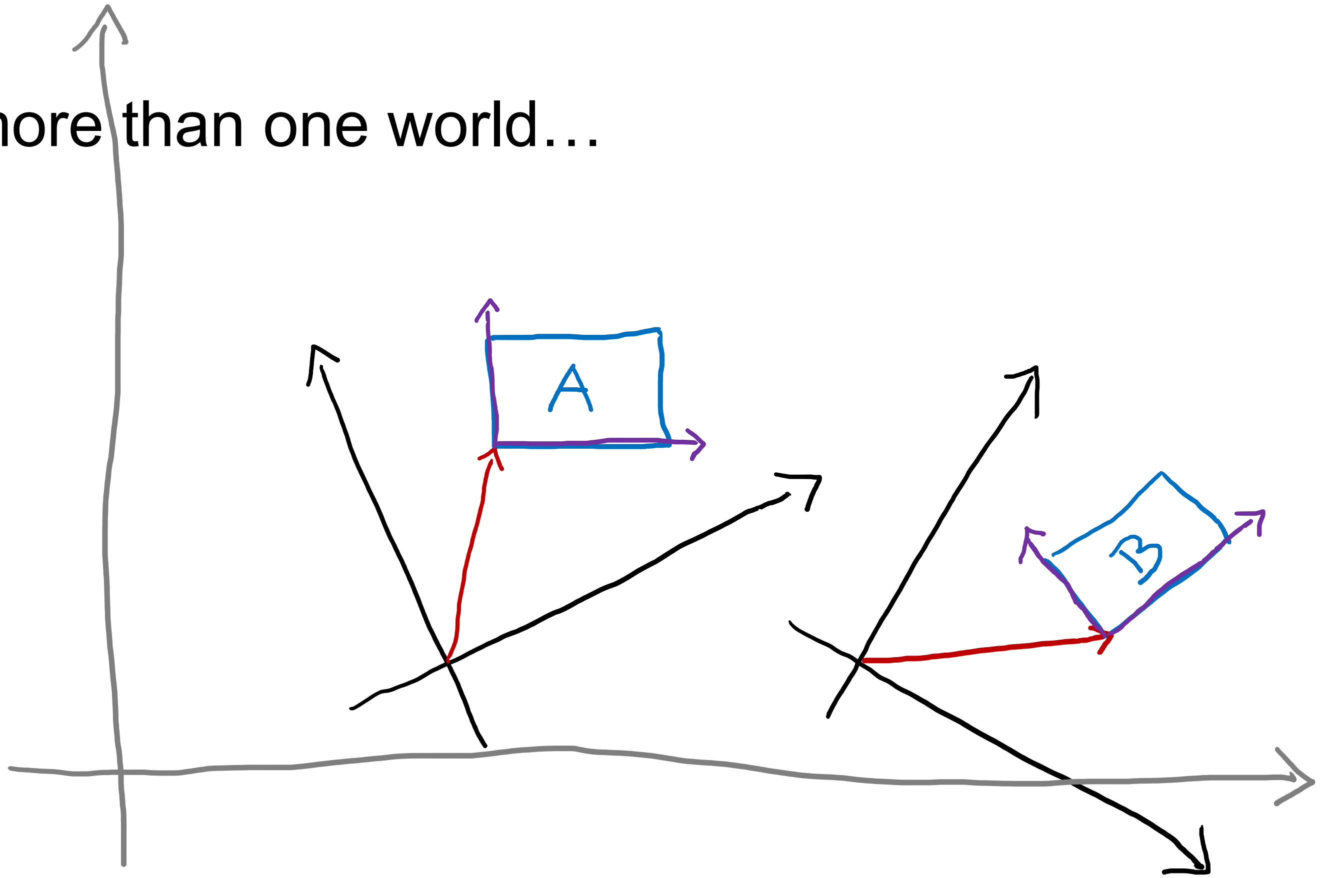
World to image

$$\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = T_{ItW}^{-1} \begin{pmatrix} X \\ Y \\ 1 \end{pmatrix}$$



Registration in World Coordinates

There is more than one world…



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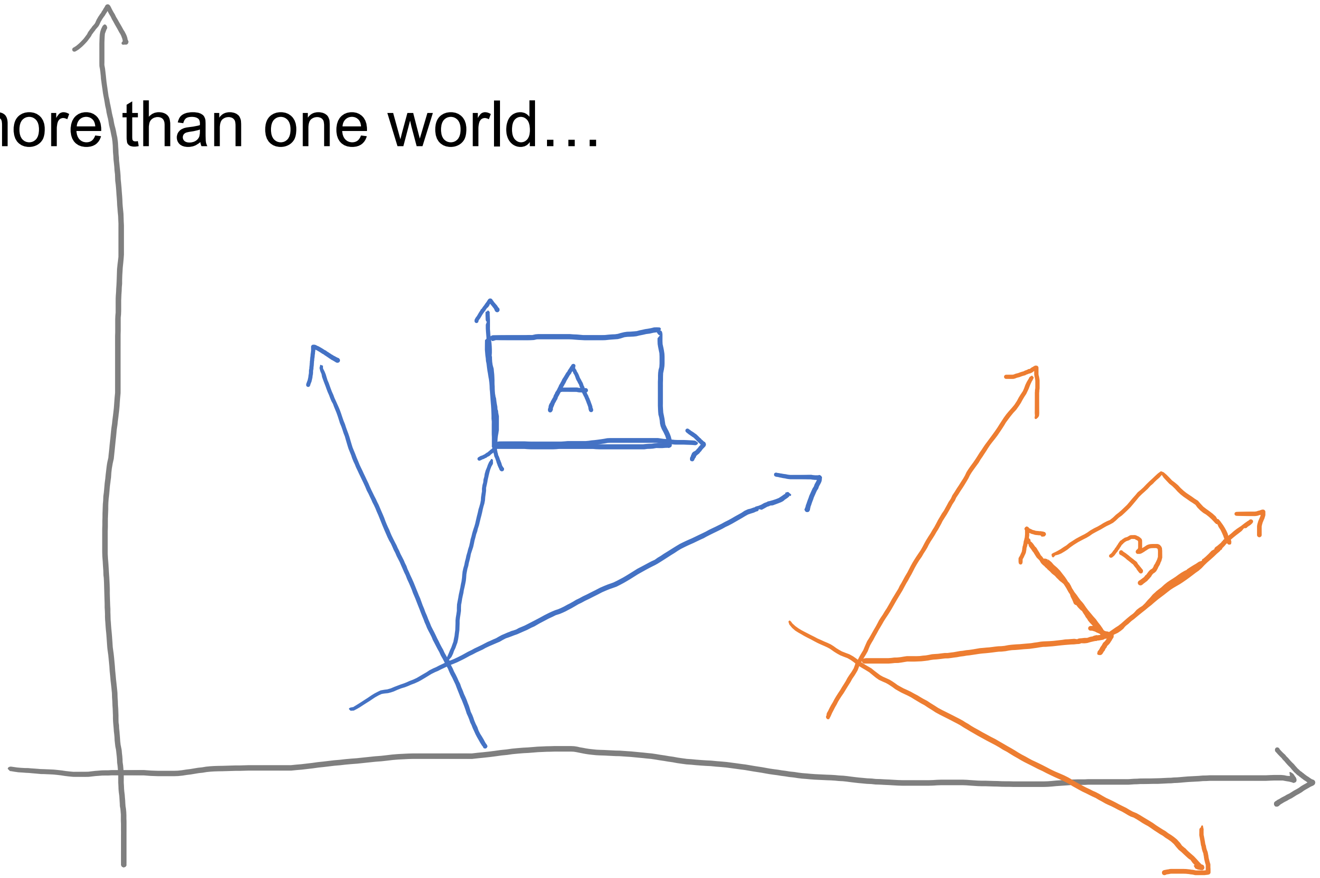

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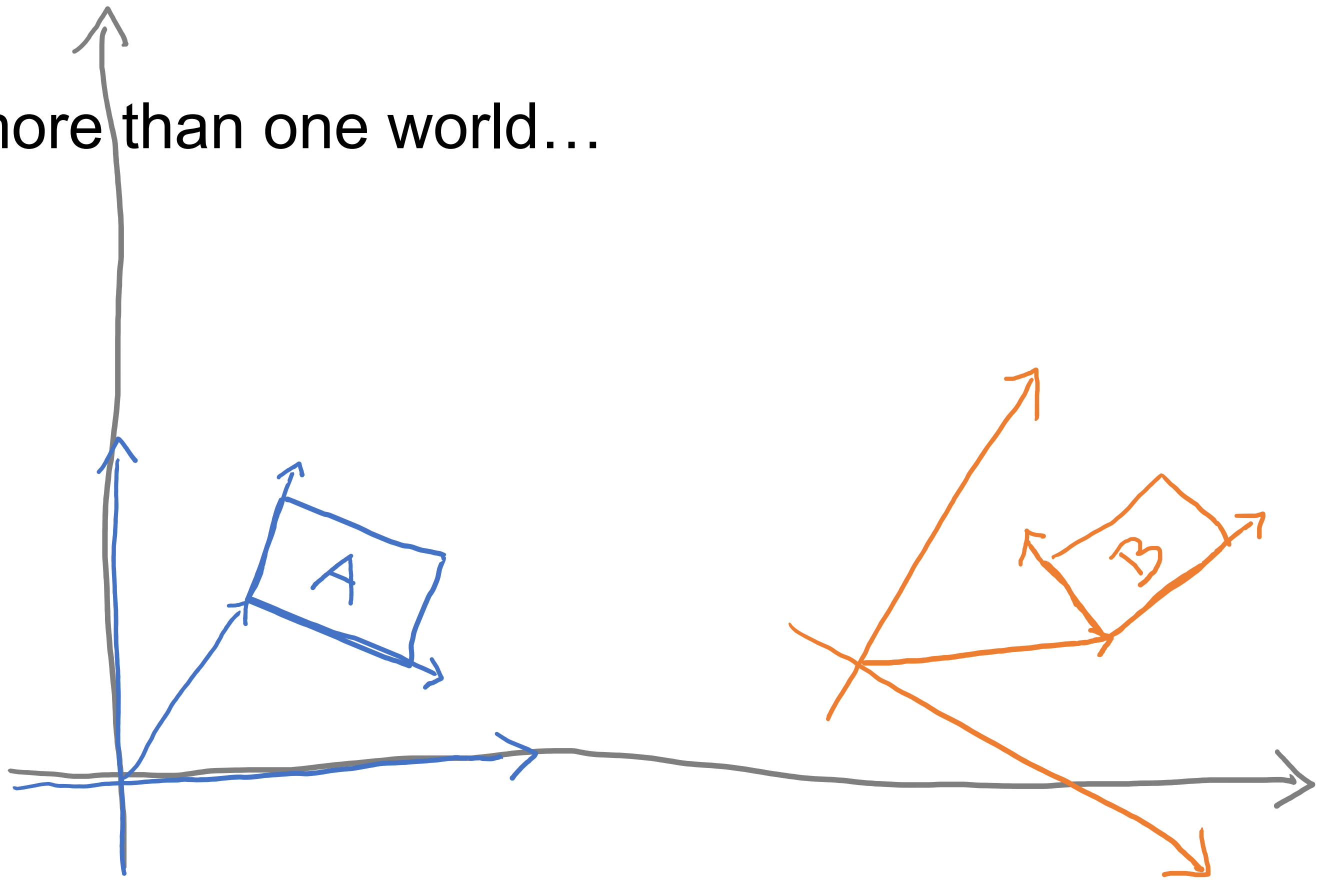

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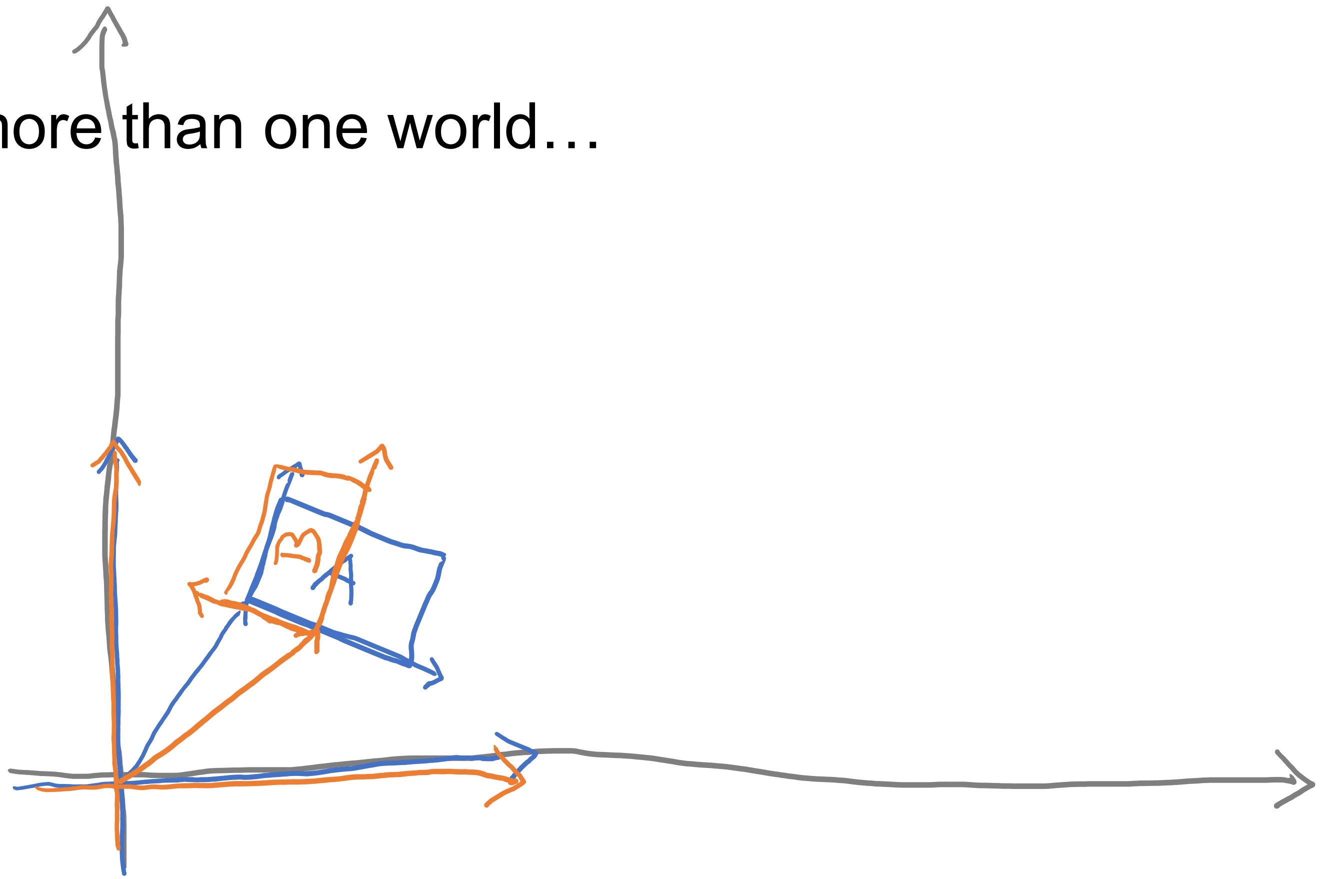

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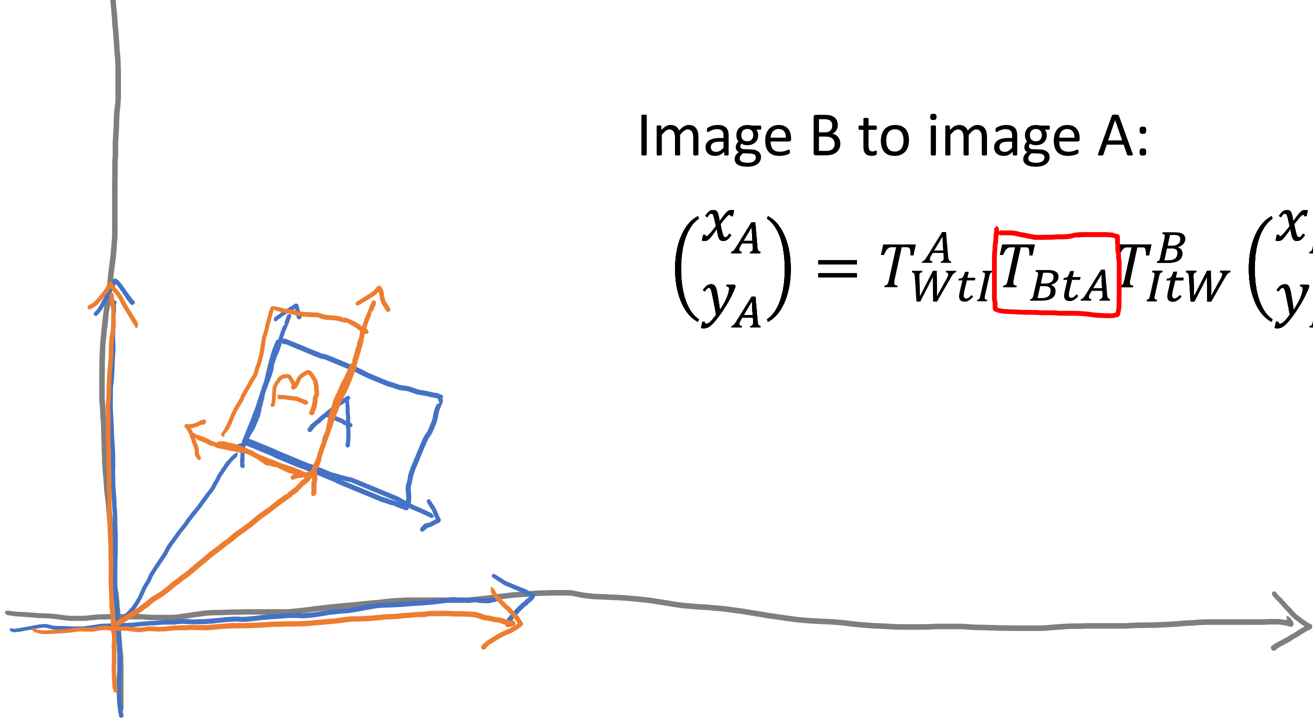


Image B to image A:

$$\begin{pmatrix} x_A \\ y_A \end{pmatrix} = T^A_{WtI} \boxed{T_{BtA}} T^B_{ItW} \begin{pmatrix} x_B \\ y_B \end{pmatrix}$$

Transformation Models

Transformation Models

linear

identity

rigid
rotation+translation

similarity
rigid+uniform scaling

affine
rigid+nonuniform scaling+shear

nonlinear

deformable

degrees of freedom / parameters

0 | 3/6 (2D / 3D) | 4/7 | 6/12 | $\underbrace{\qquad}$ thousands/millions

- poly-affine
- parameterised deformation

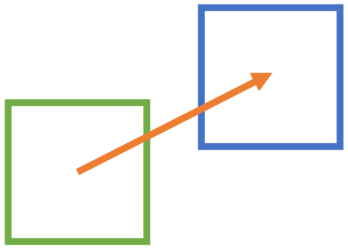
Linear Transformations

Parameterisation of linear transformation using **homogeneous coordinates**

2D affine: translation (2), rotation (1), scaling (2), shear(1) = 6 DOF

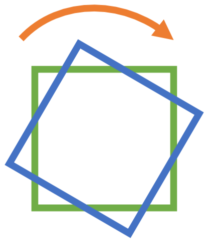
Translation

$$T = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix}$$



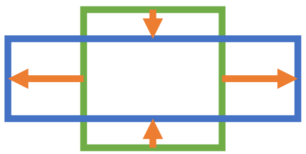
Rotation

$$R = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$



Scaling

$$S = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix}$$



Shearing

$$H = \begin{bmatrix} \cos\omega & \sin\omega & 0 \\ -\sin\omega & \cos\omega & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

?

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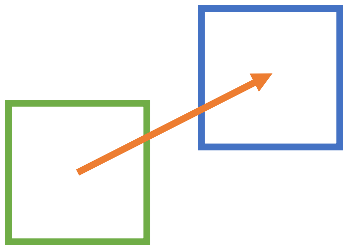

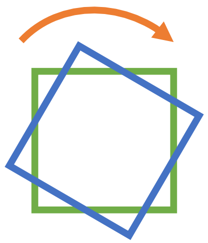

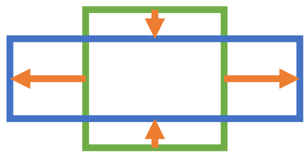

$$H\, S\, H^{-1}$$

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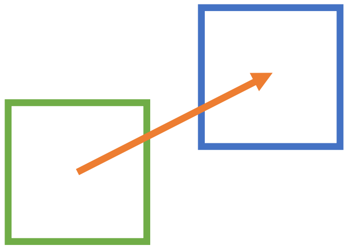

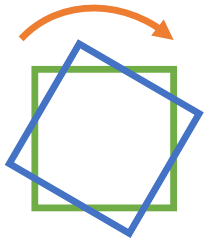

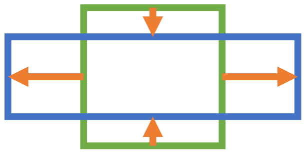

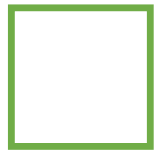

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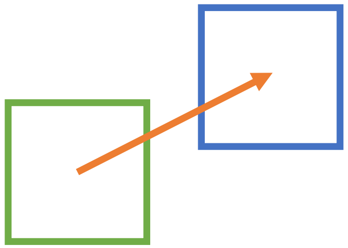

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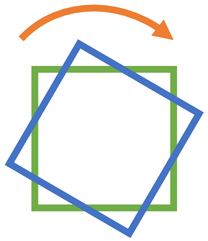

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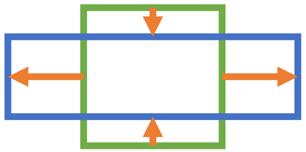

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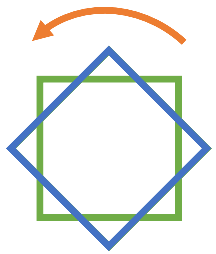

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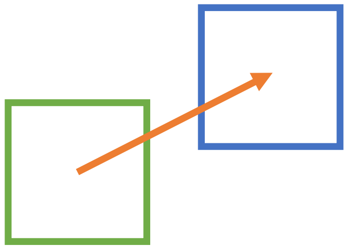

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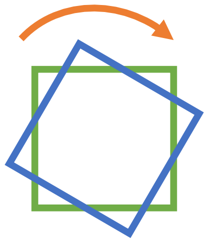

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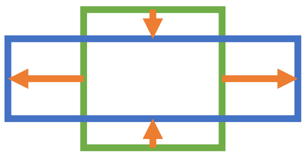

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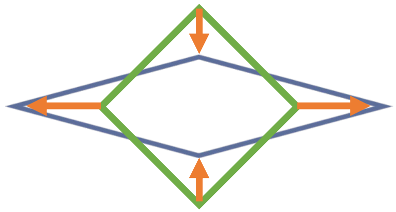

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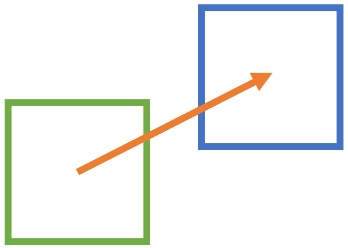

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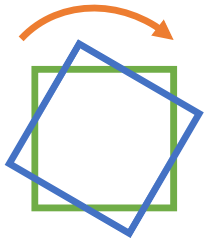

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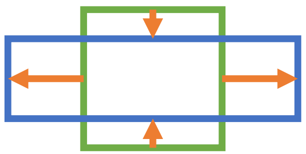

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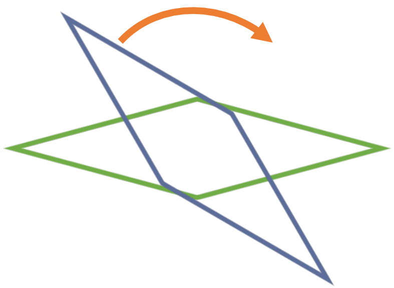

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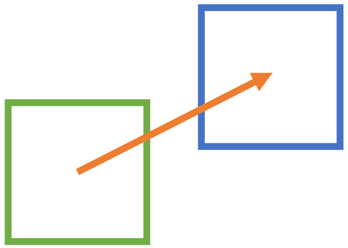

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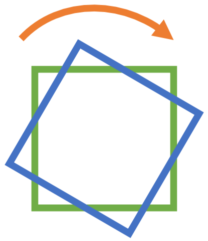

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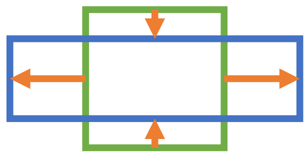

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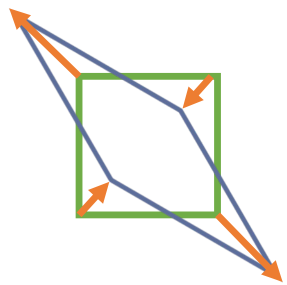

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Shearing

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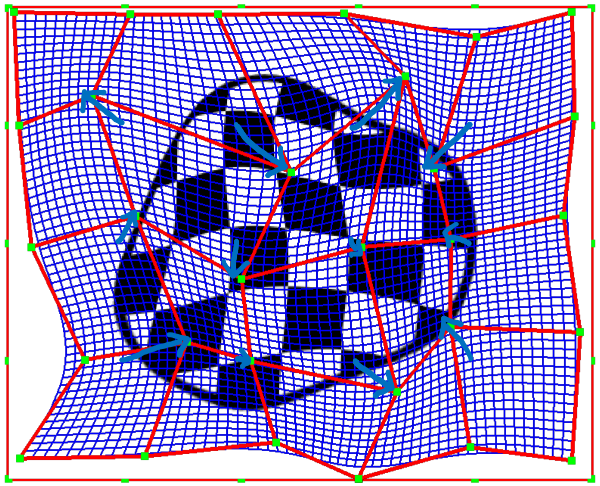
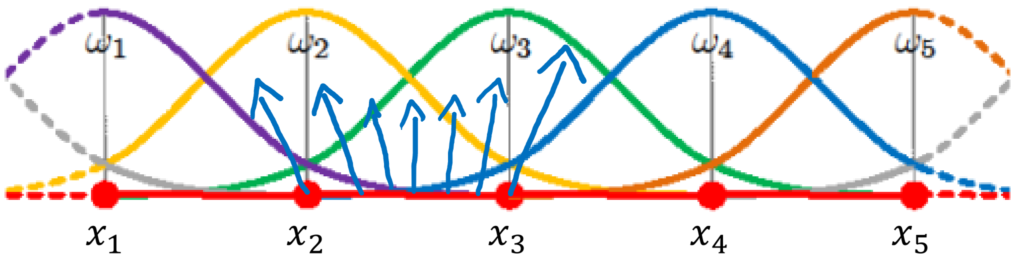
$$A = H\,S\,H^{-1} R\,T = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ 0 & 0 & 1 \end{bmatrix}$$

Free-Form Deformations

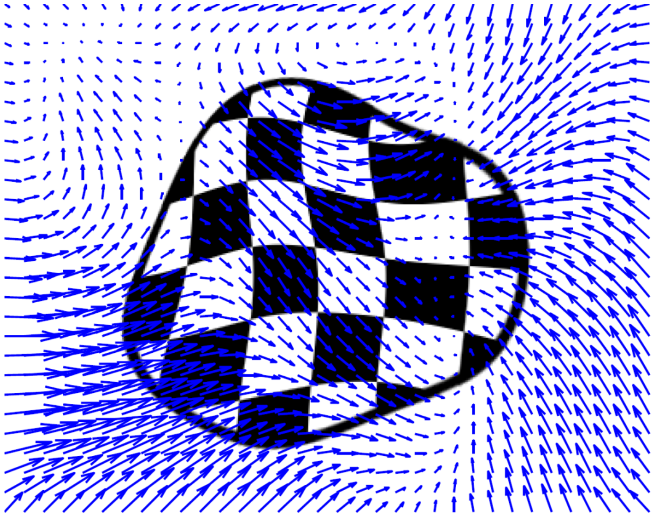
Low-dimensional deformation model

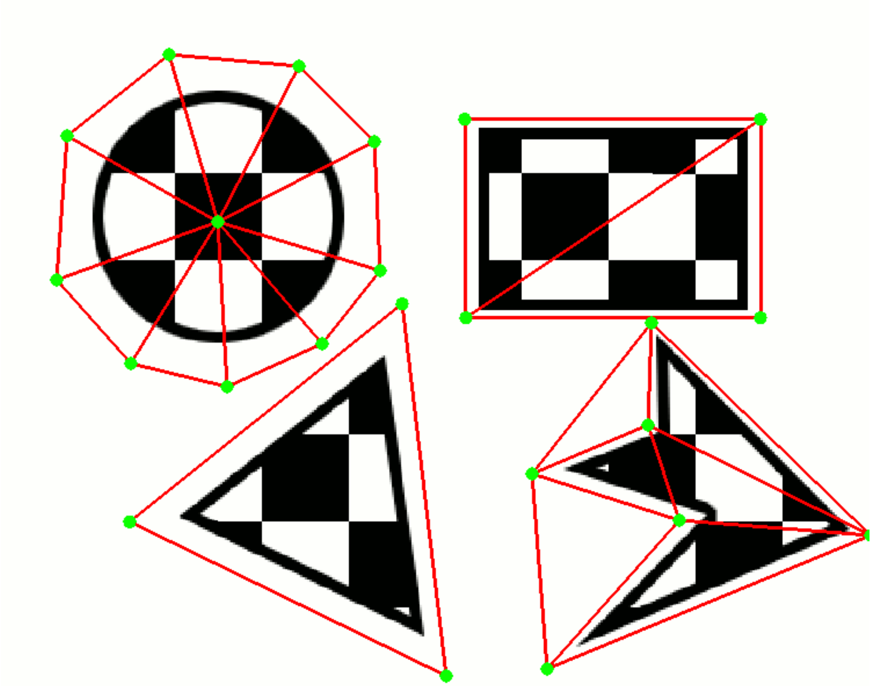




Other Deformation Models

- Control point based models
- Finite-element methods
- Dense displacements fields

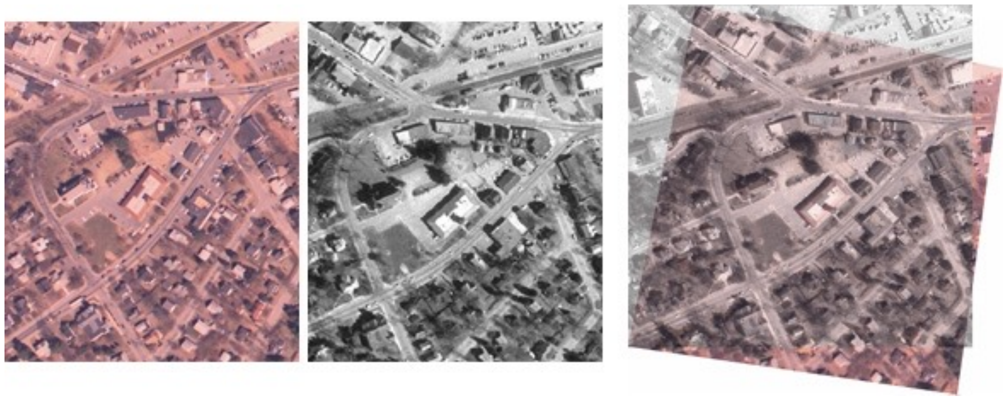




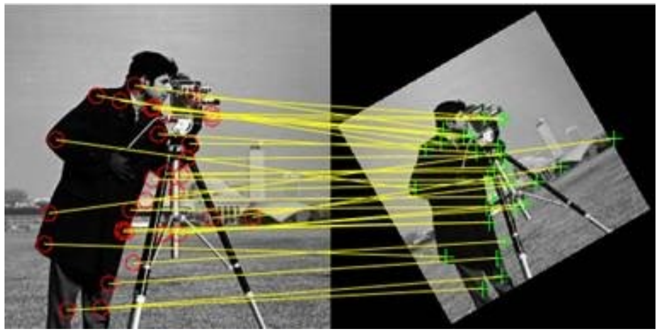
Applications

Image Registration Applications

Satellite Imaging



Point Correspondences

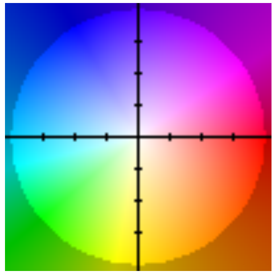


Source: https://uk.mathworks.com/discovery/image-registration.html

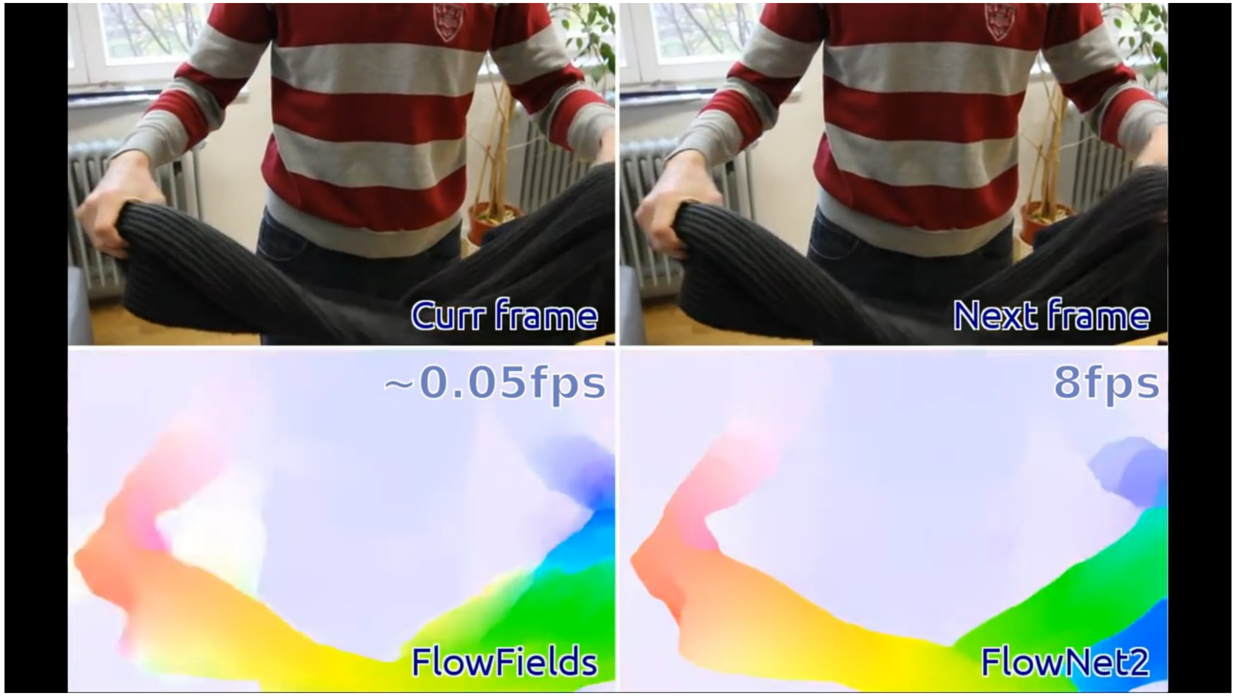
Image Registration Applications

Panoramic Image Stitching

Image Registration Applications



Optical Flow

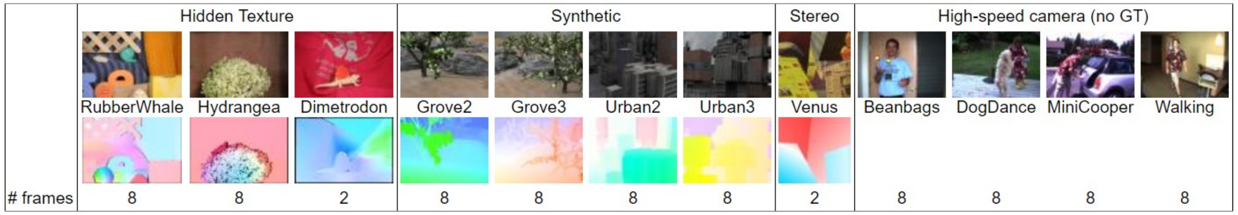


http://vision.middlebury.edu/flow/

https://youtu.be/JSzUdVBmQP4

Datasets for Optical Flow

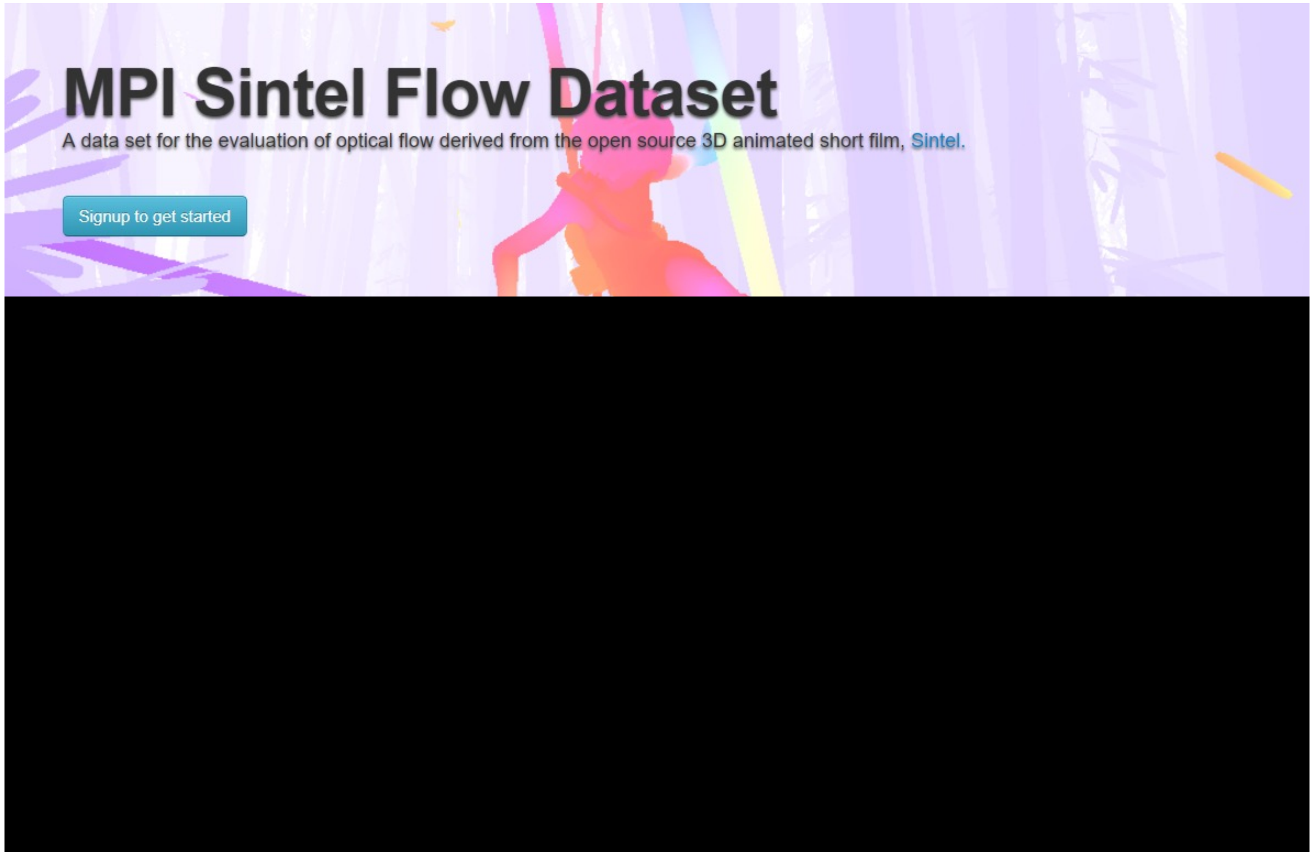
- Middlebury
  http://vision.middlebury.edu/flow/



- KITTI Vision Benchmark Suite
  http://www.cvlibs.net/datasets/kitti/

Datasets for Optical Flow

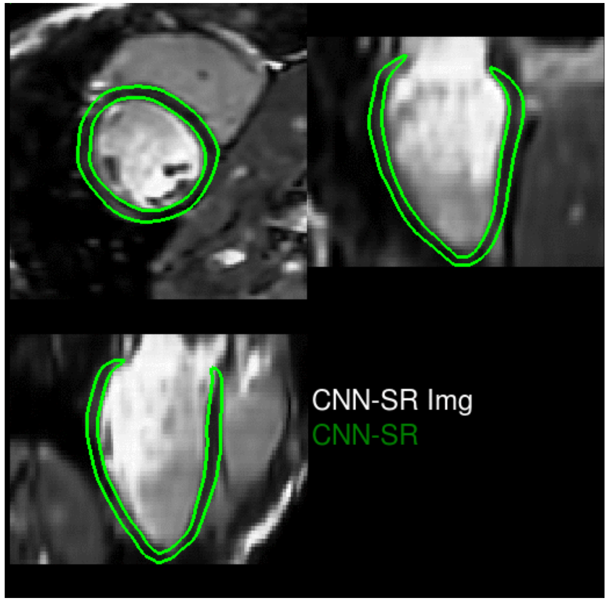
- Sintel
  http://sintel.is.tue.mpg.de/



https://youtu.be/ZmiBI4tPk_o

Medical Imaging Applications

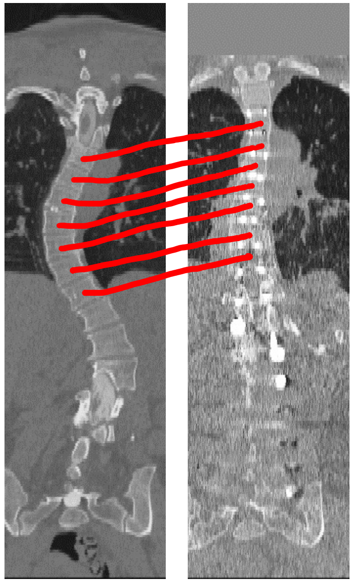
Cardiac Motion

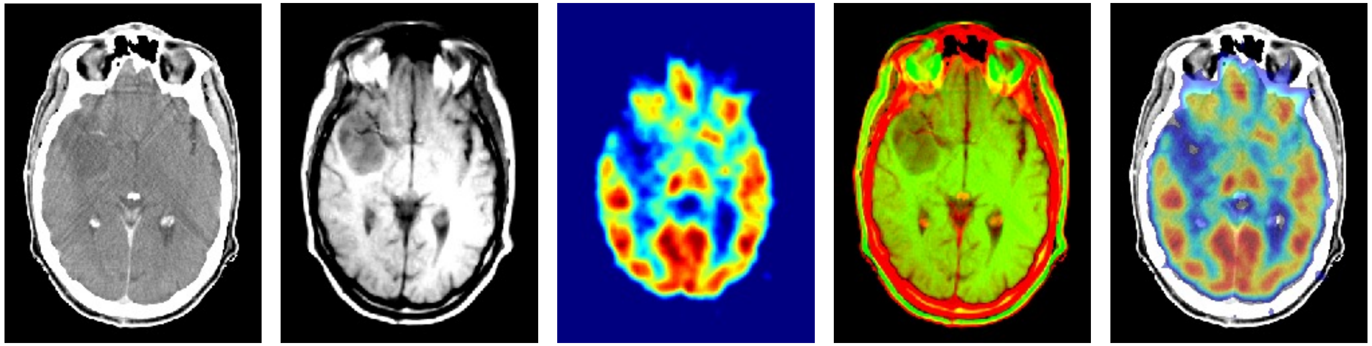


Source: Oktay et al. MICCAI 2016

Respiratory Motion

Pre- and post-op



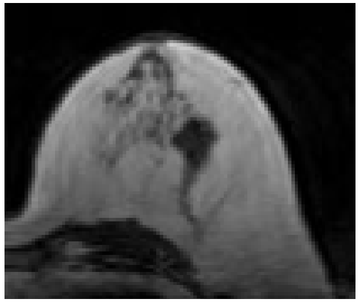


Multi-modal Image Fusion

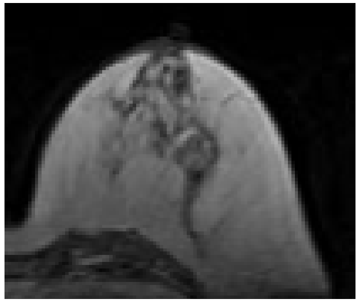
Intra-subject Registration

Contrasted and non-contrasted images [Rueckert et al. 1999]

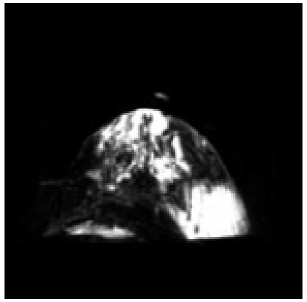
non-contrast

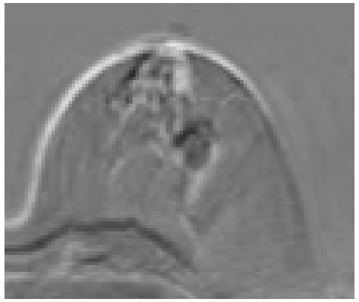


contrast

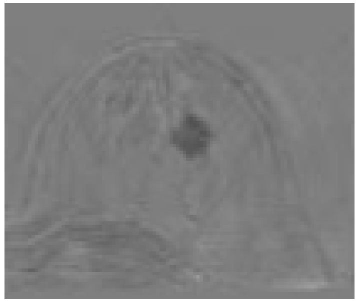


MIP before

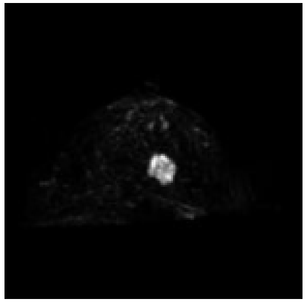




difference image
before registration



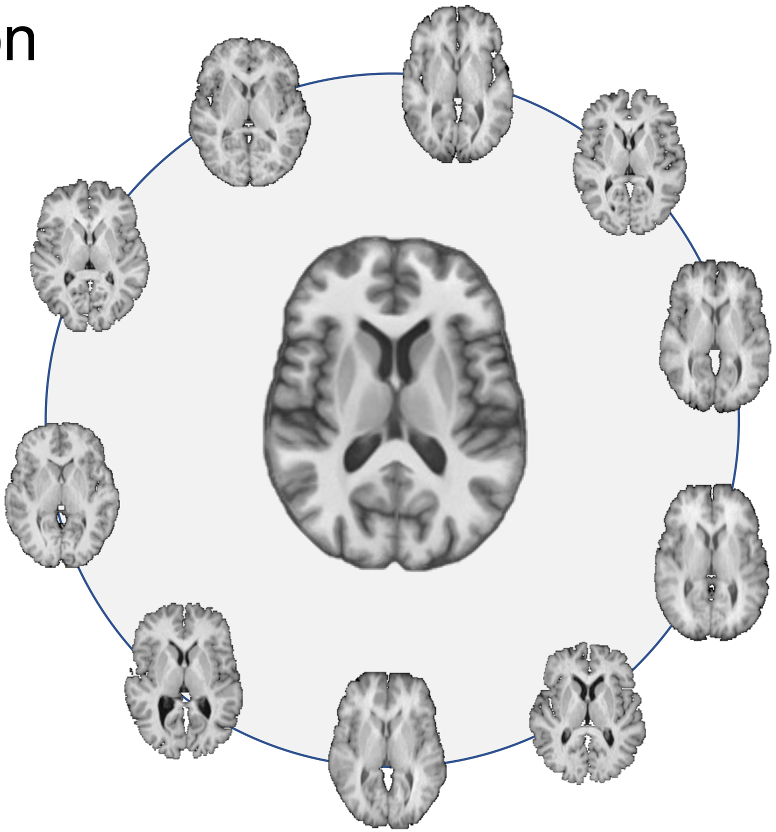
difference image
after registration



MIP after

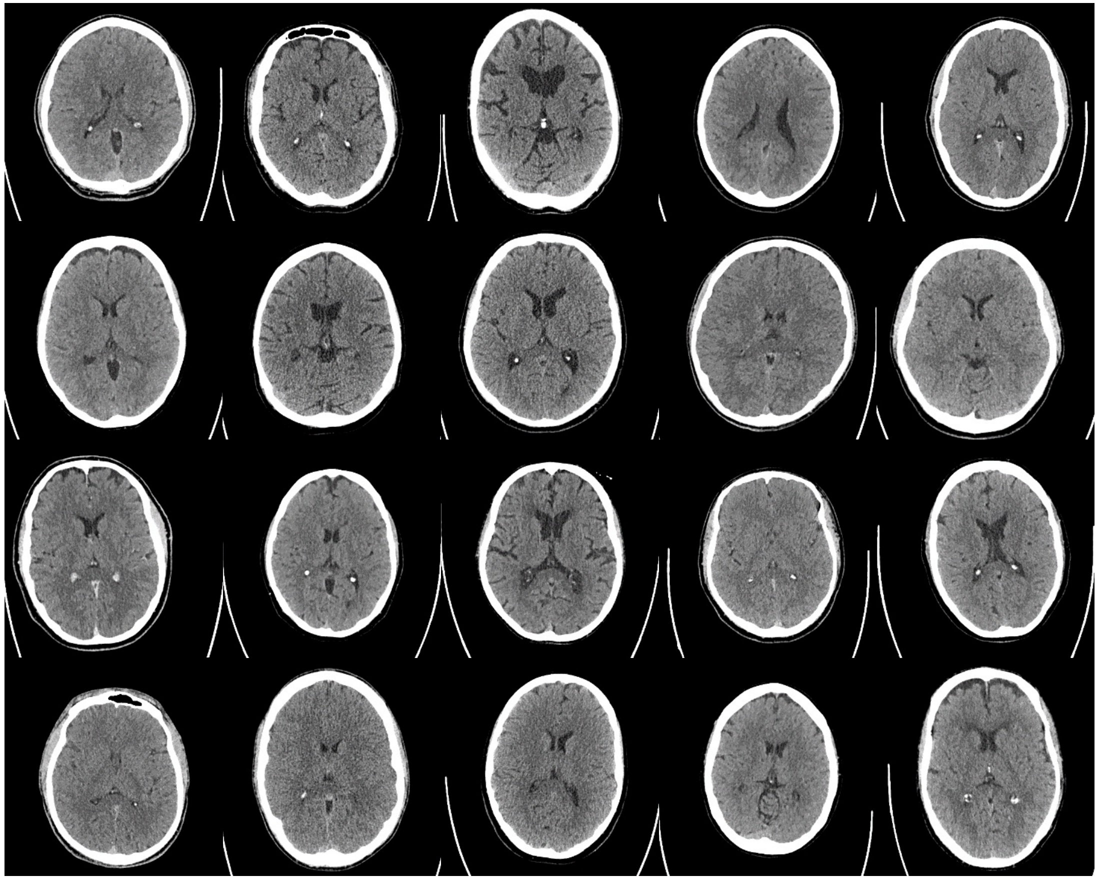
Inter-subject Registration

Atlas construction

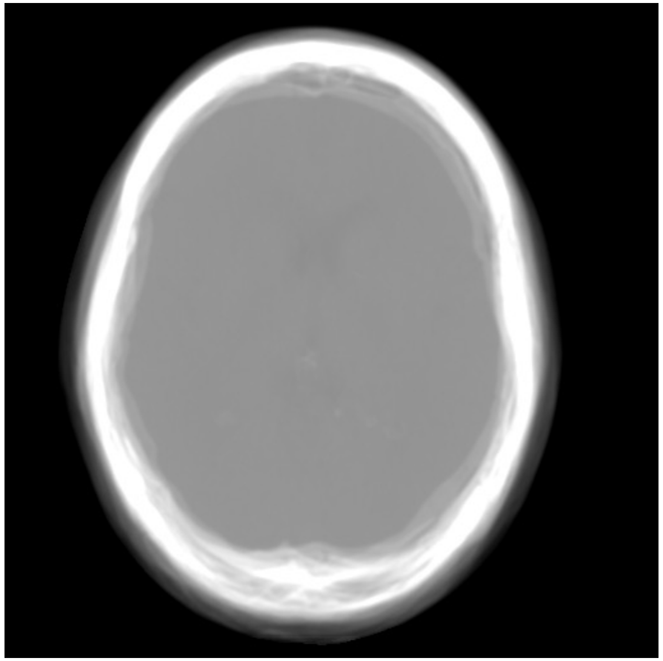


Input data

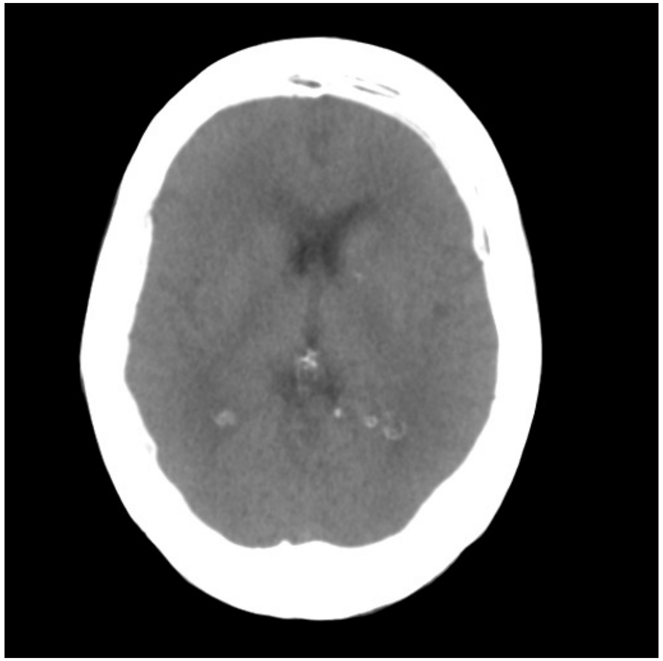
- 20 random subjects from ‘normal CT’ database
- One selected as ‘target’
- Iterative registration
  1) Rigid
  2) Affine
  3) Nonrigid



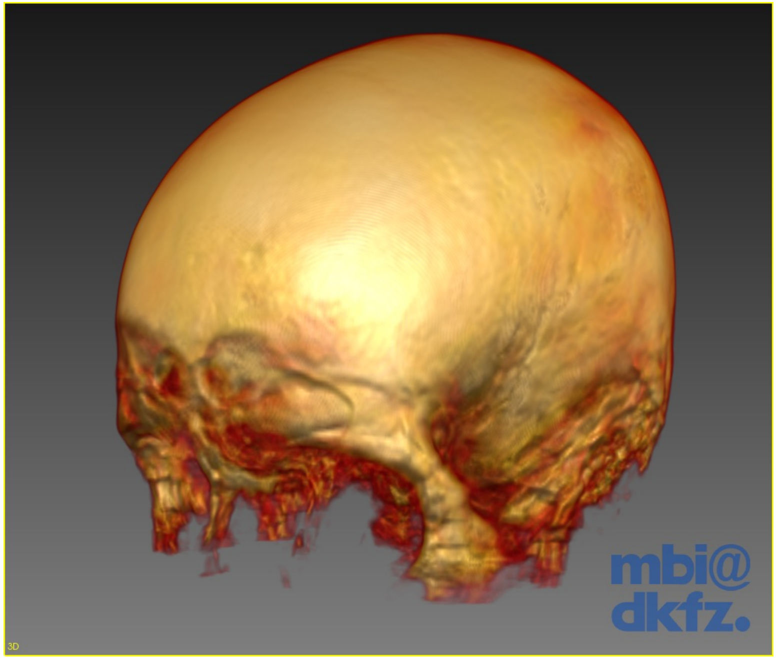
Atlas Iterations: Step 1 – Rigid



average image
full range

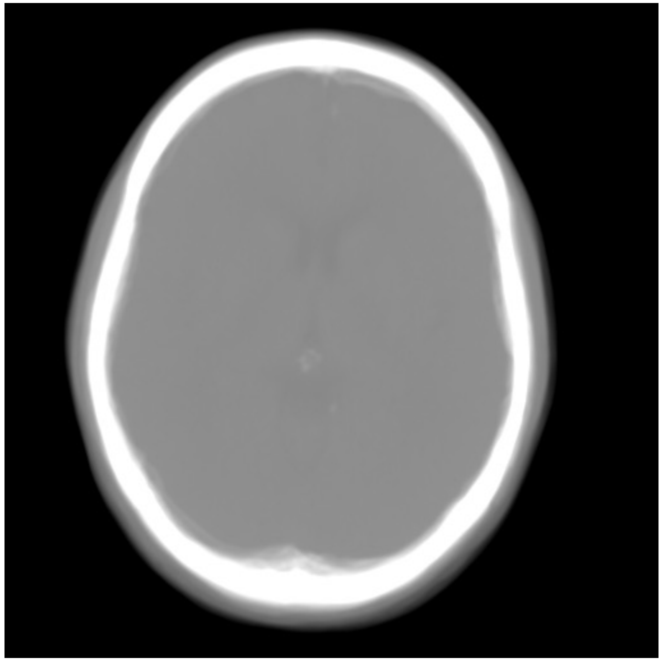


average image
bone window

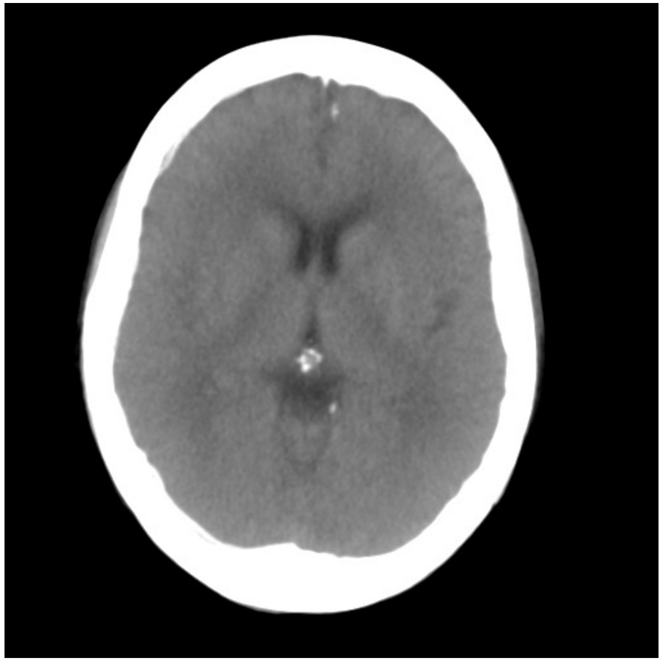


average image
volume rendering

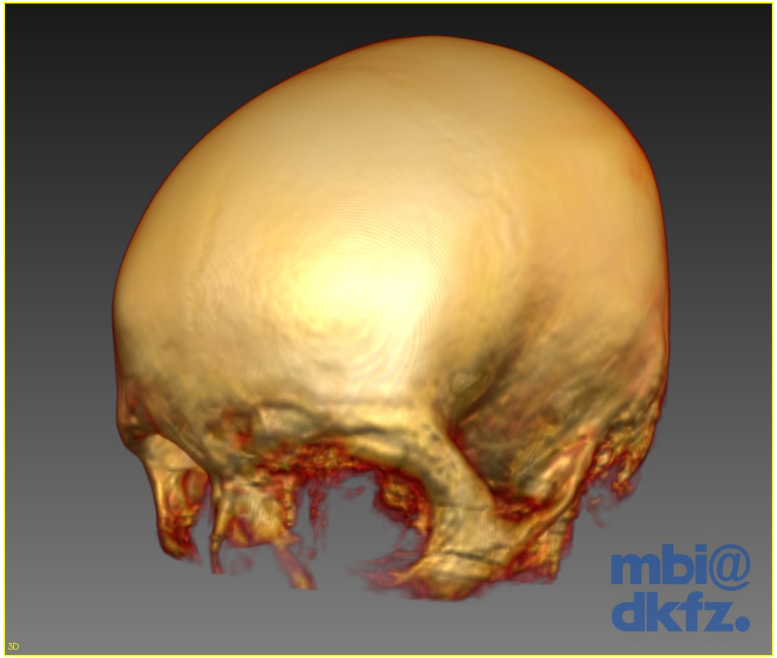
Atlas Iterations: Step 2 – Affine



average image
full range

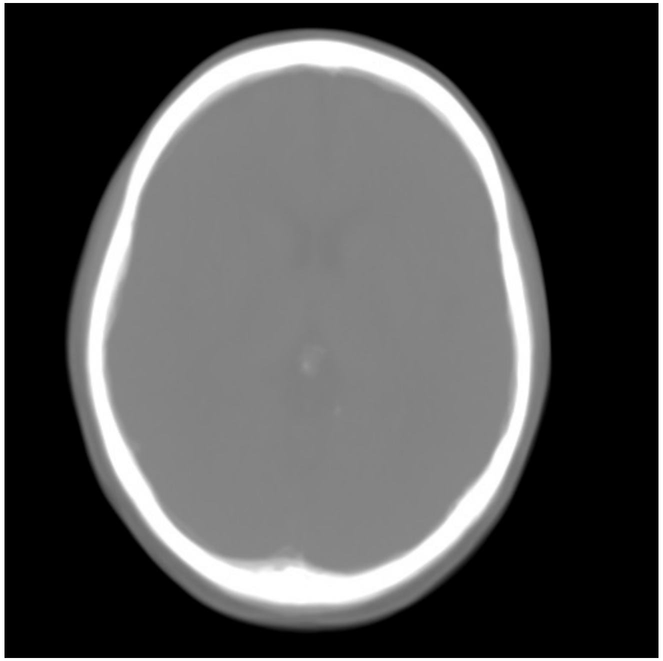


average image
bone window

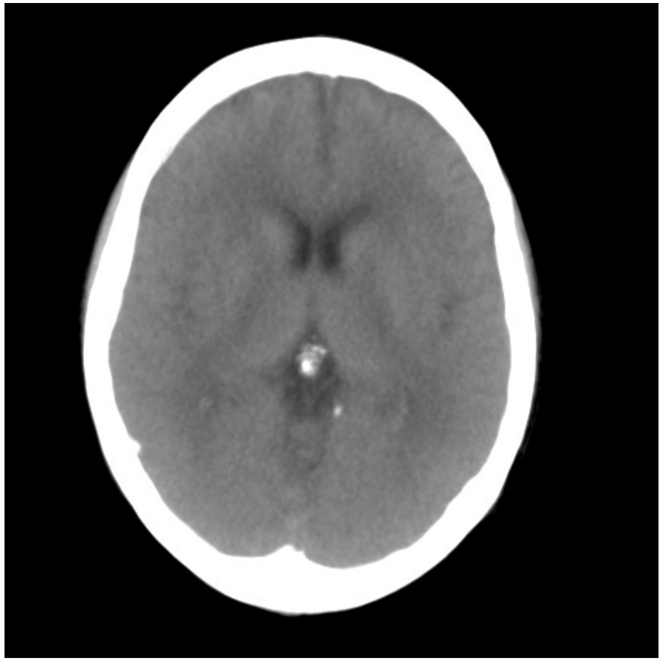


average image
volume rendering

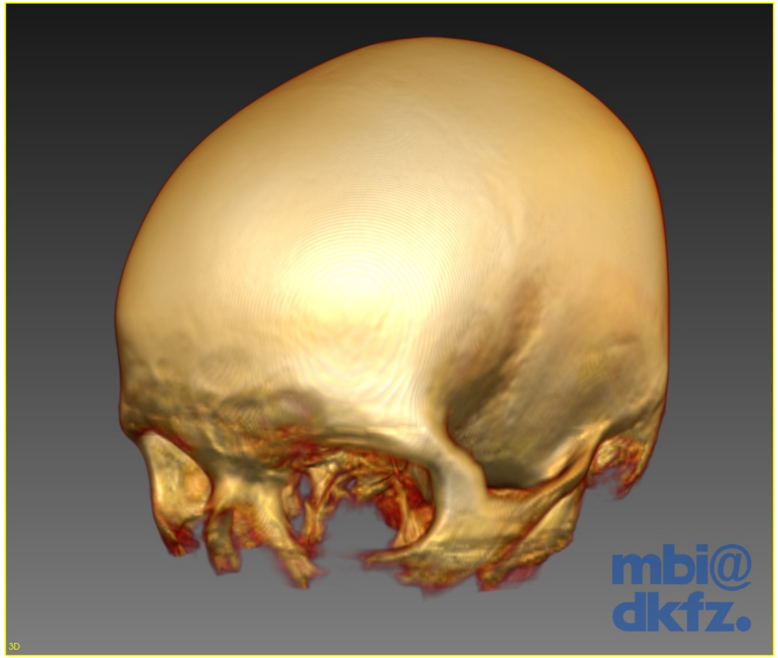
Atlas Iterations: Step 3 – Nonrigid



average image
full range

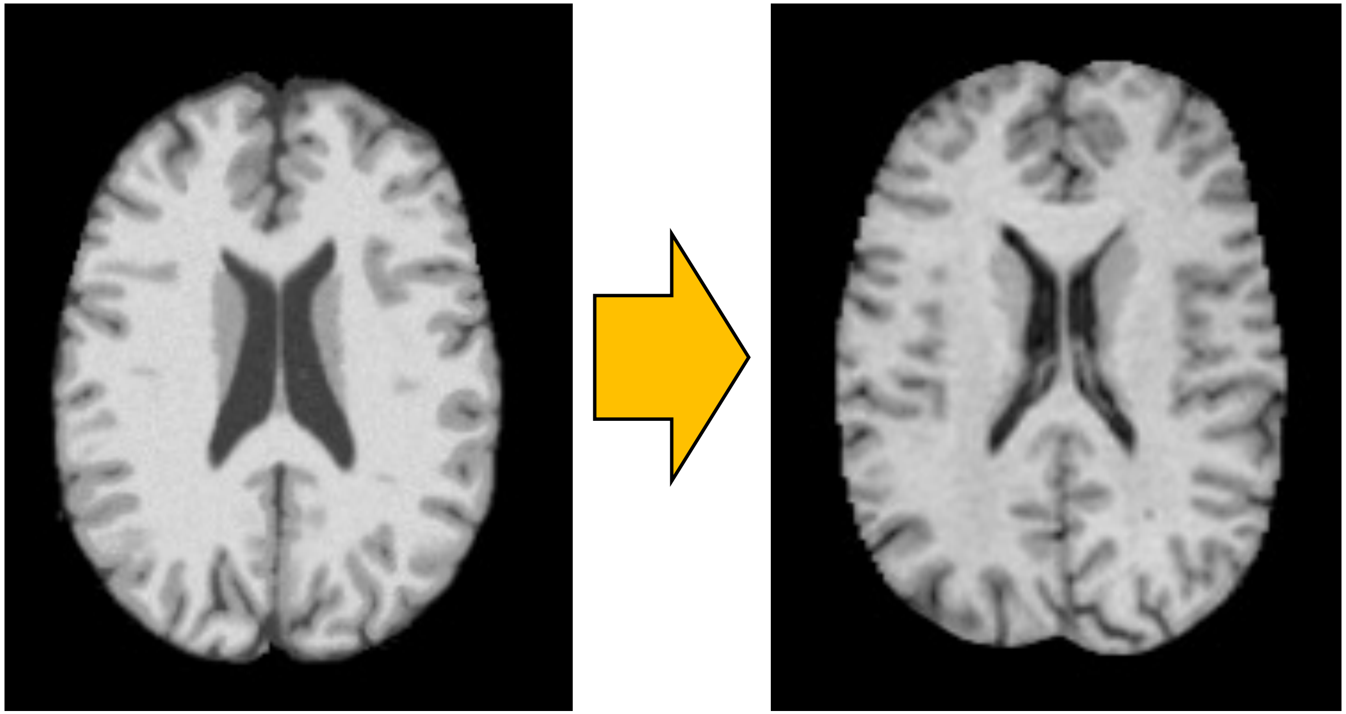


average image
bone window

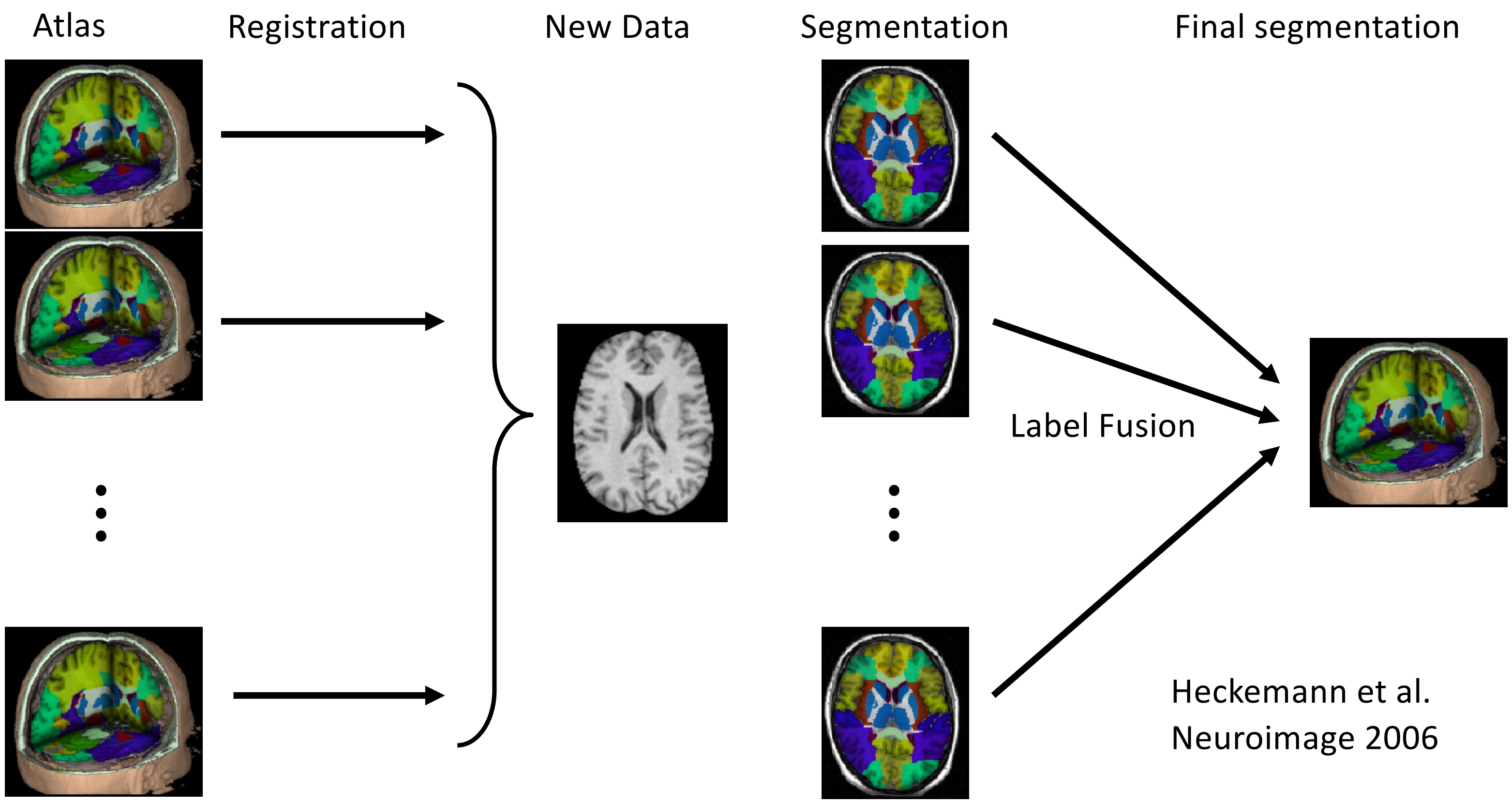


average image
volume rendering

Segmentation using Registration



Multi-Atlas Label Propagation

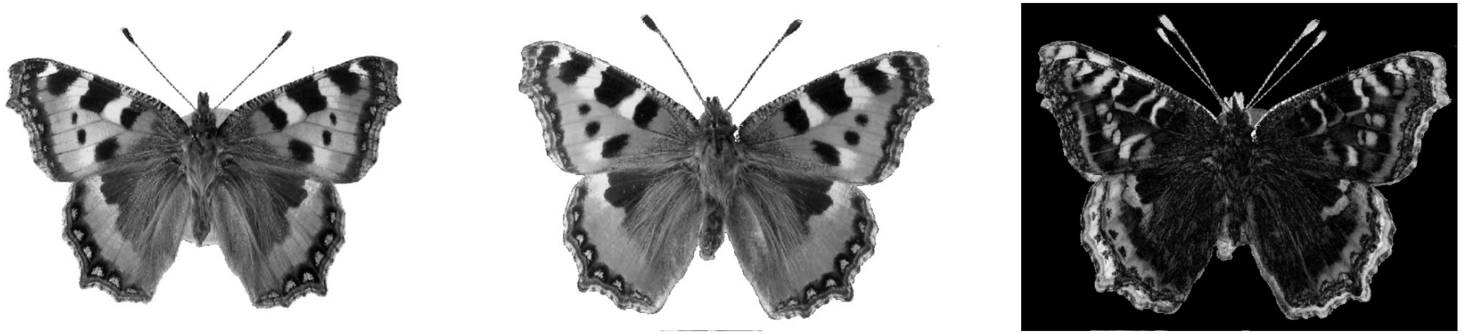


Heckemann et al.
Neuroimage 2006

Intensity-based Registration

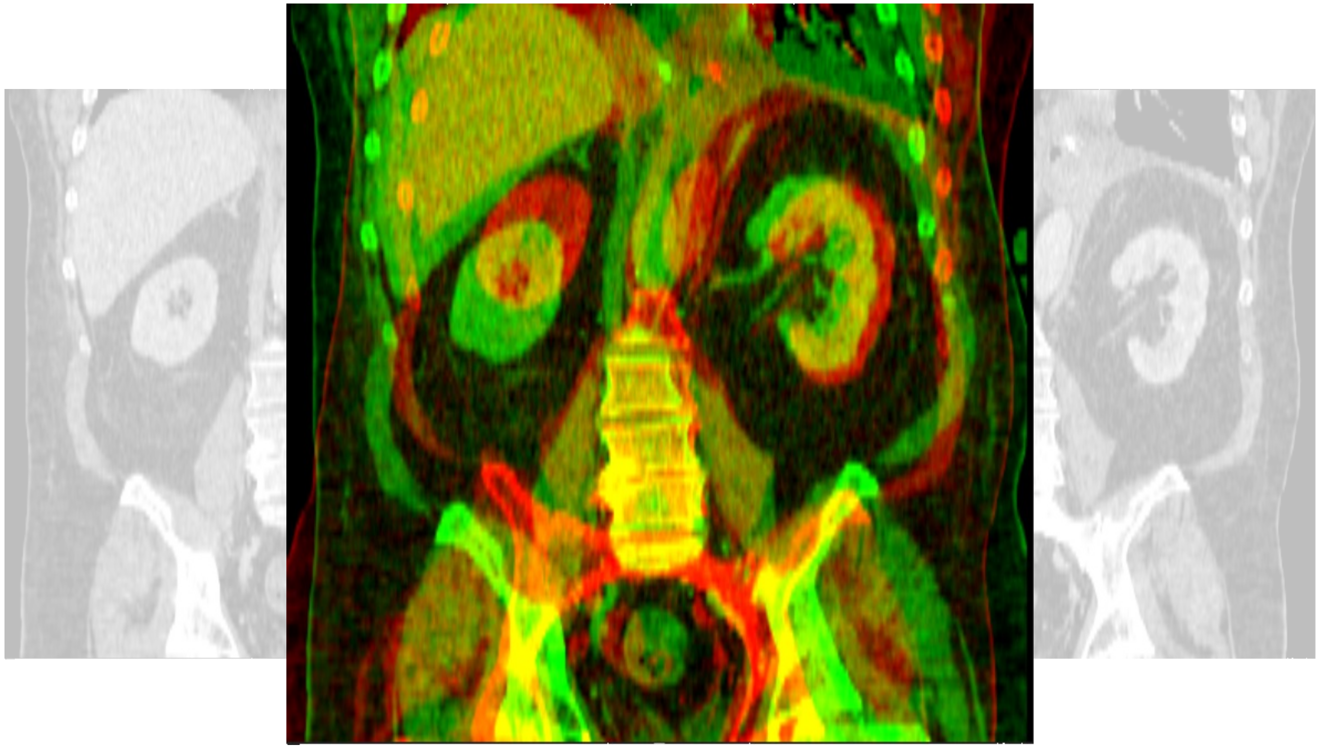
Intensity-based Registration

- Estimation of transformation parameters is driven by the appearance of the images
- Images are registered when they appear similar



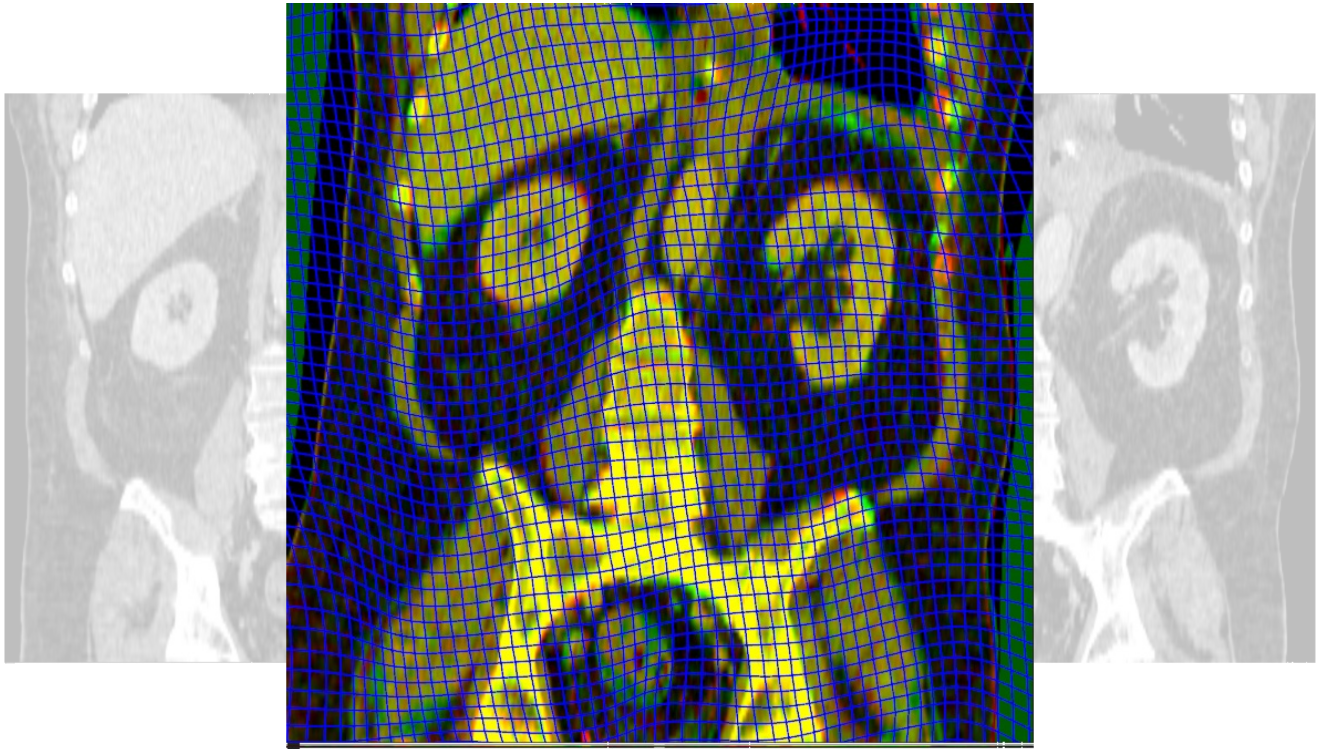
Intensity-based Registration

Intensity-based Registration

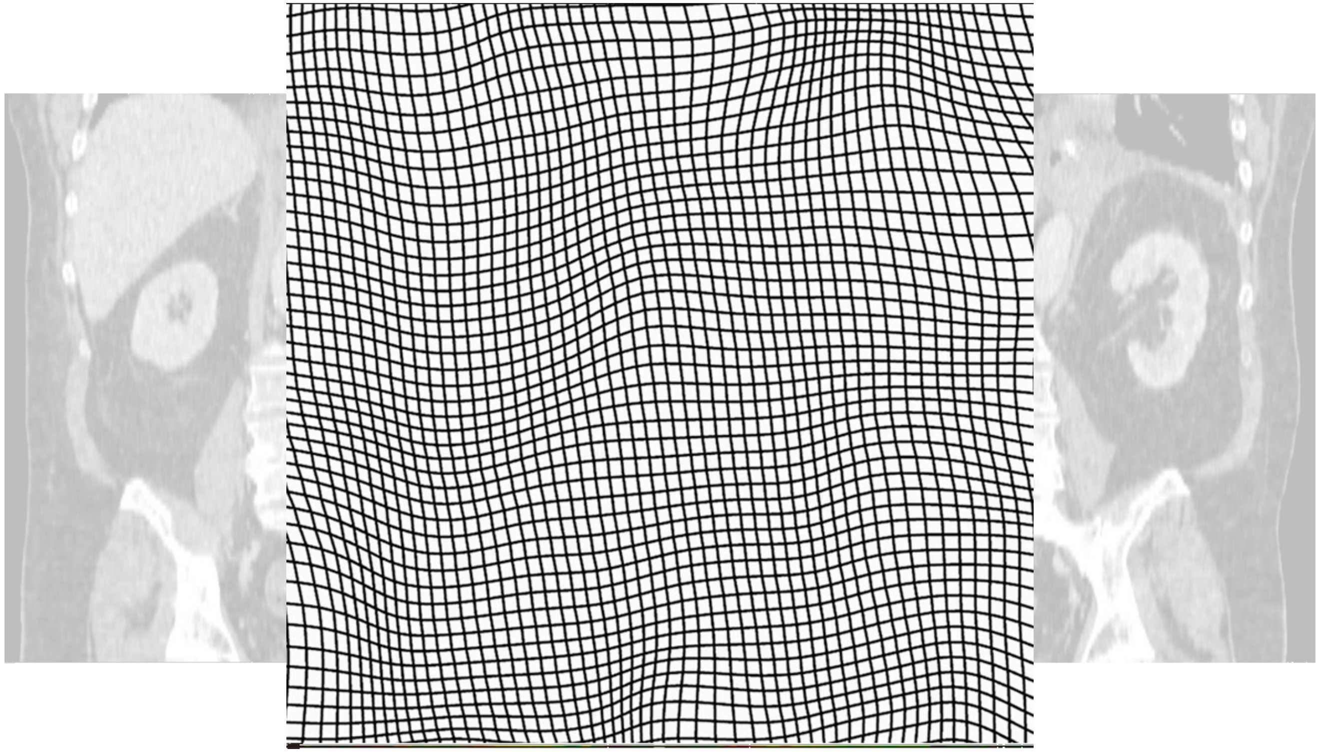


Intensity-based Registration

Intensity-based Registration

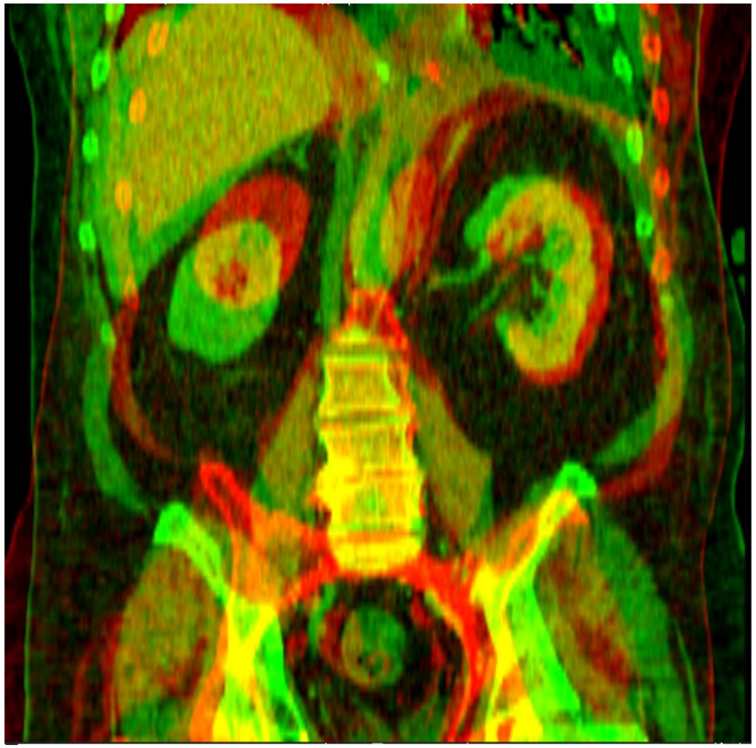


Intensity-based Registration

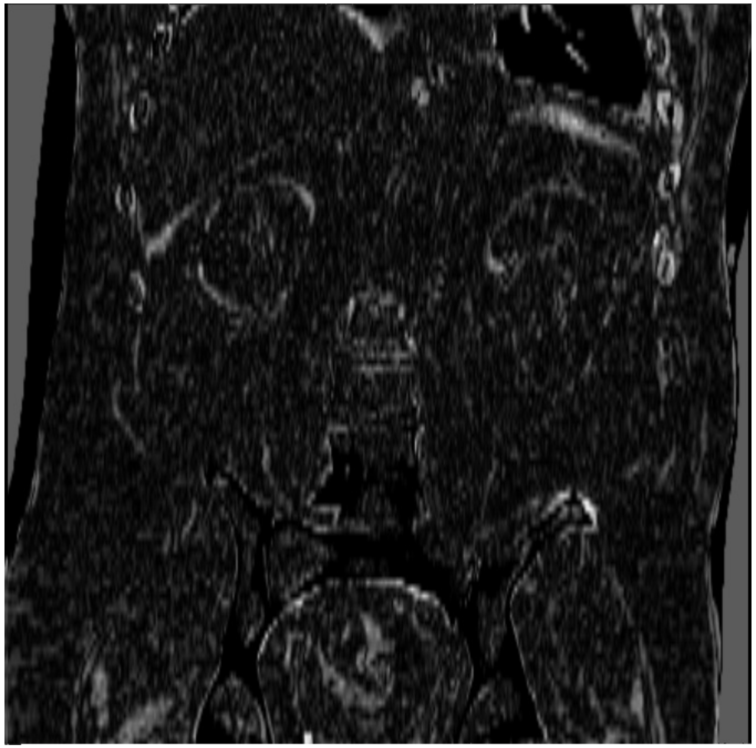


Intensity-based Registration

Intensity-based Registration



Intensity-based Registration



Intensity-based Registration

Objective function, cost function, energy function

$$C(\underset{\text{transformation}}{T}) = \underset{\text{dissimilarity measure}}{D}(\underbrace{I \circ T}_{\text{moving image}}, \underset{\text{fixed image}}{J})$$

Intensity-based Registration

Optimisation problem

$$\hat{T} = \arg\min_{T} C(T)$$

return
the argument
(not the value)

search T
with minimum
cost value

cost function
$C : \mathbb{R}^{d} \to \mathbb{R}$

d.o.f./parameters
of transform

Mono-modal vs Multi-modal

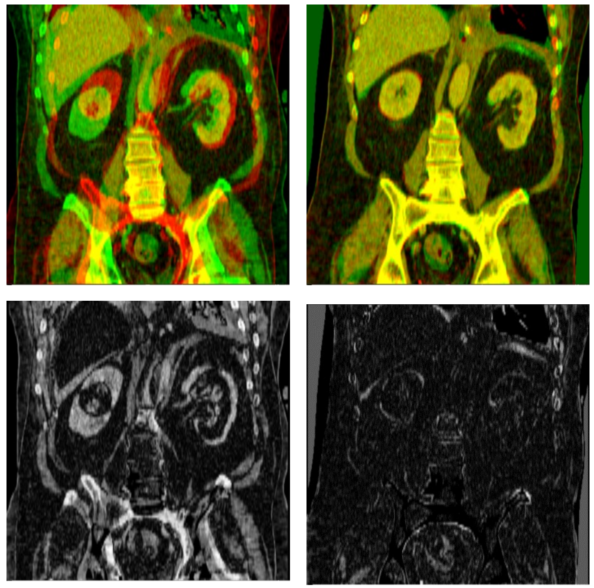
Mono-modal registration

- Image intensities are related by a (simple) function

Multi-modal registration

- Image intensities are related by a complex function or statistical relationship

(Dis)similarity Measures



Intensity differences

Sum of squared differences (SSD)

$$D_{SSD}(I \circ T, J) = \frac{1}{N} \sum_{i=1}^{N} (I(T(x_i)) - J(x_i))^2$$

Sum of absolute differences (SAD)

$$D_{SAD}(I \circ T, J) = \frac{1}{N} \sum_{i=1}^{N} |I(T(x\_i\ )) - J(x\_i)|$$

Assumption: identity relationship between intensity distributions

Application: mono-modal registration (e.g. CT-CT)

(Dis)similarity Measures

Correlation coefficient (CC)

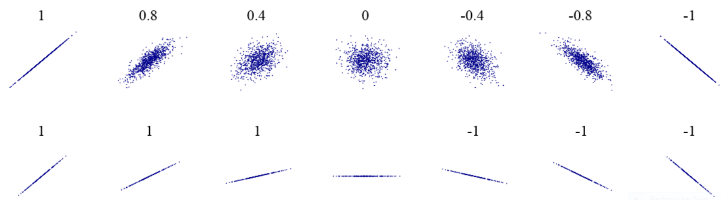
$$D_{CC}(I \circ T, J) = -\frac{\overbrace{\frac{1}{N}\sum_{i=1}^{N}\left(I(T(x_i)) - \mu_I\right)\left(J(x_i) - \mu_J\right)}^{cov(I,J)}}{\underbrace{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I\left(T(x_i)\right) - \mu_I\right)^2}}_{\sigma_I}\underbrace{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(J(x_i) - \mu_J\right)^2}}_{\sigma_J}}$$

μ_I: mean intensity of image I

μ_J: mean intensity of image J

Assumption: linear relationship between intensity distributions

Application: (mainly) mono-modal registration (e.g. MR-MR)



(Dis)similarity Measures

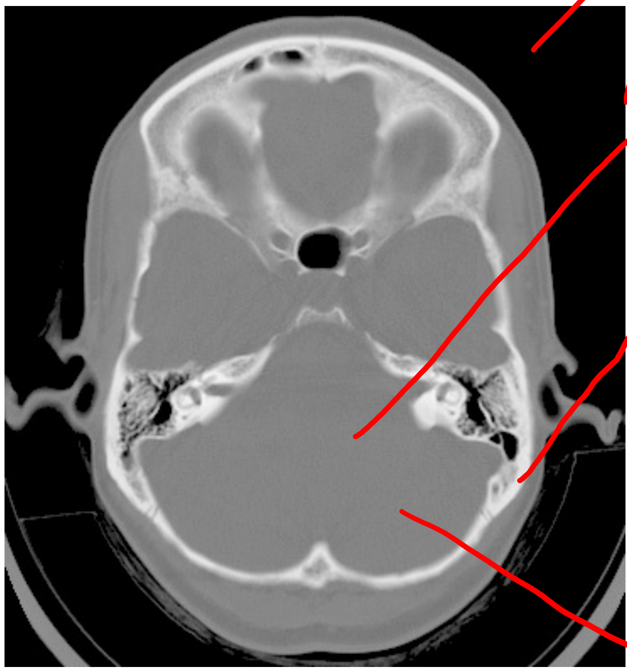
Statistical relationship

air

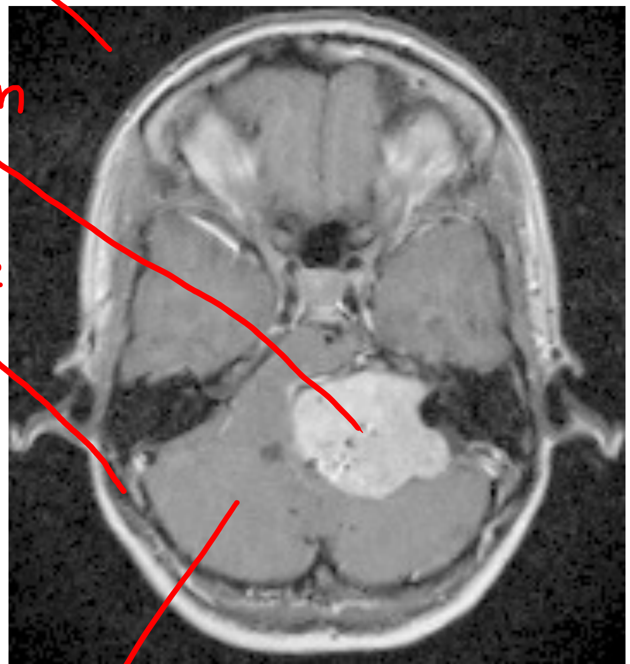
lesion

bone

soft tissue



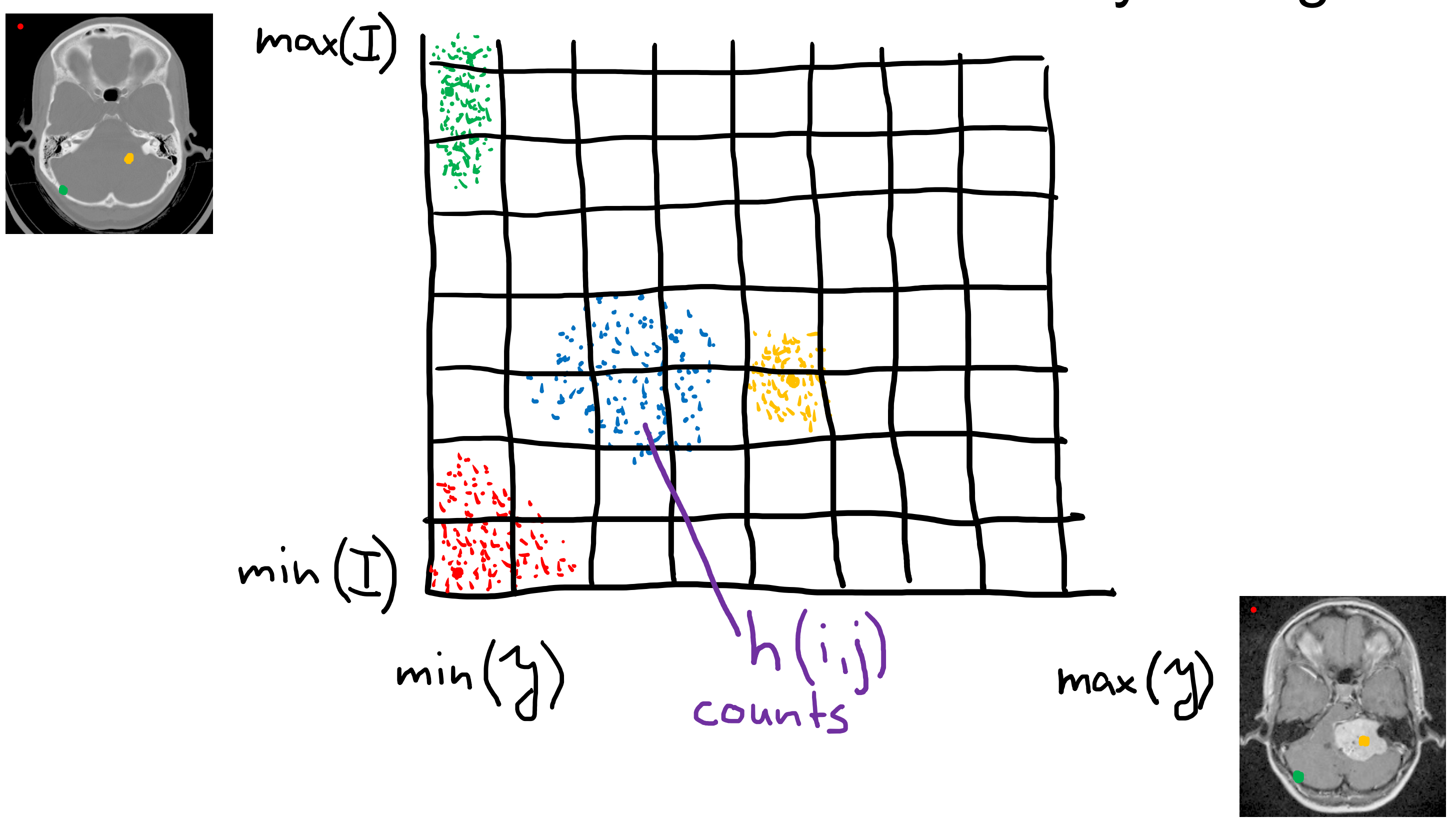
CT



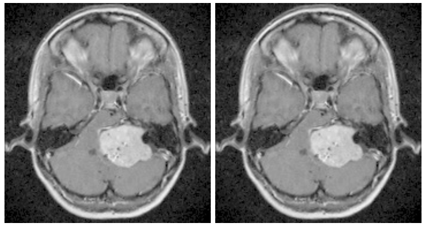
MR

(Dis)similarity Measures

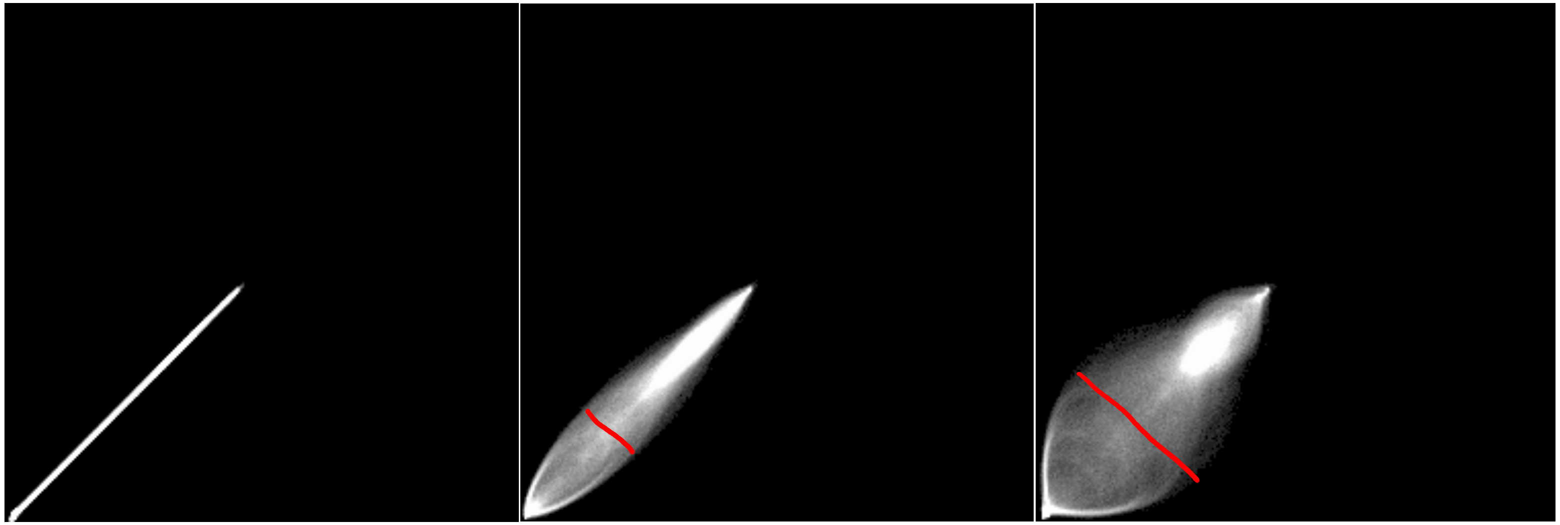
2D intensity histograms



(Dis)similarity Measures

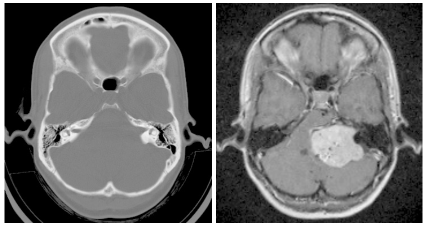


MR/MR

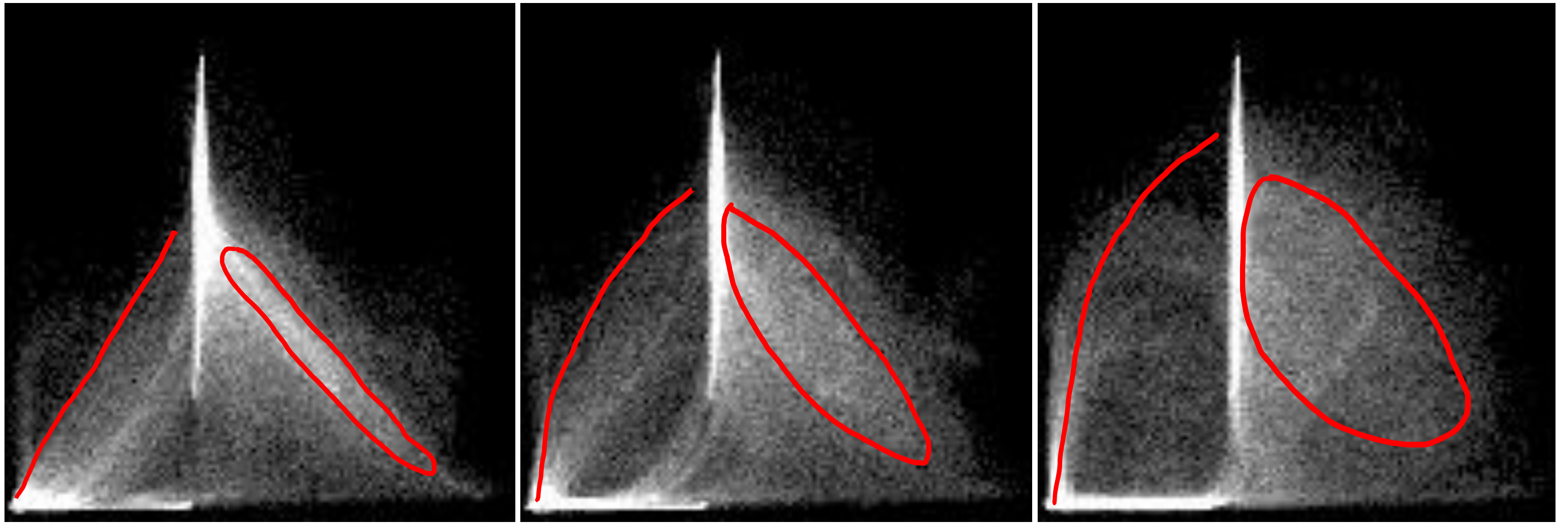


registered | misregistered by 2mm | misregistered by 5mm

(Dis)similarity Measures

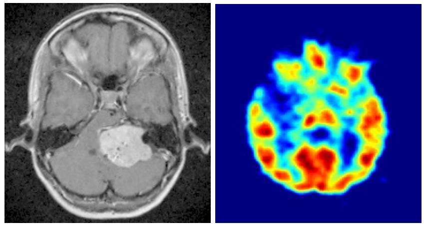


CT/MR

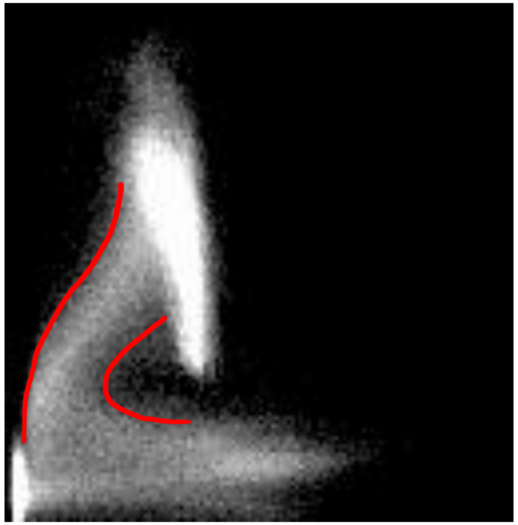


registered | misregistered by 2mm | misregistered by 5mm

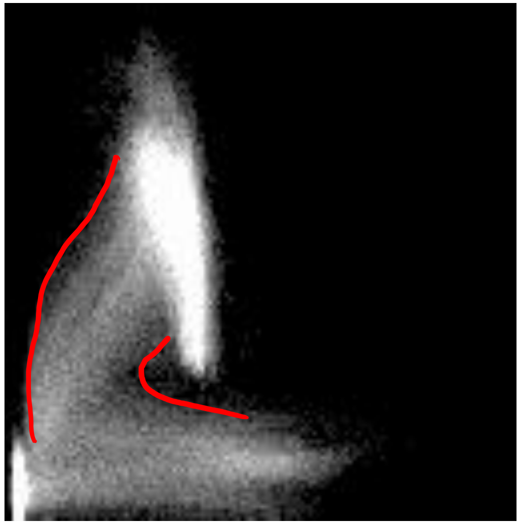
(Dis)similarity Measures



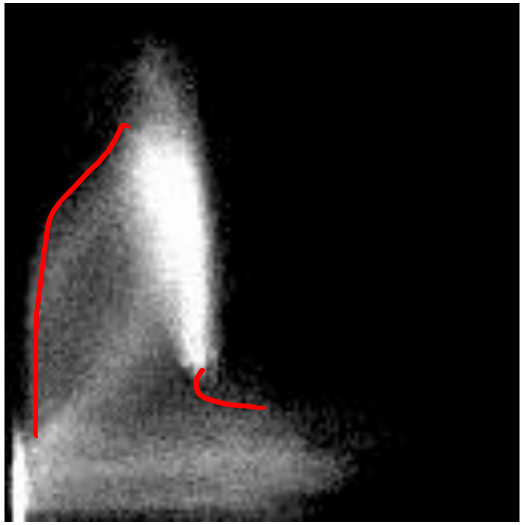
MR/PET



registered



misregistered by 2mm



misregistered by 5mm

(Dis)similarity Measures

Intensity distributions

$$p(i,j) = \frac{h(i,j)}{N}$$ – counts in histogram

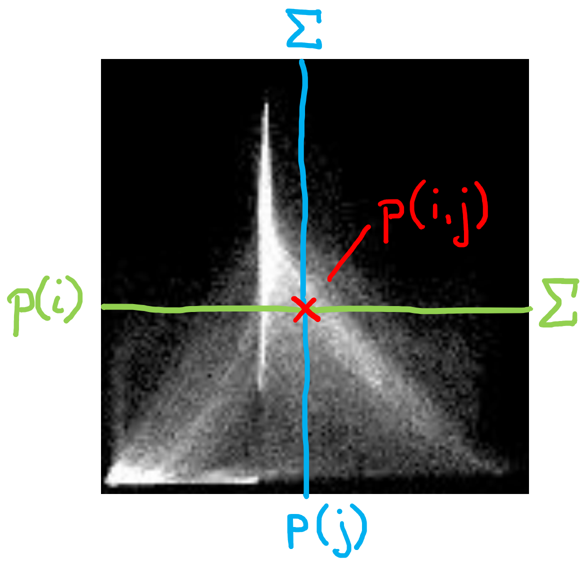
joint probability of an image point
having a value i in image I and value j in image J

$$p(i) = \sum_j p(i,j)$$

marginal probability of an image point
having a value i in image I

$$p(j) = \sum_i p(i,j)$$

marginal probability of an image point
having a value j in image J



(Dis)similarity Measures

Shannon entropy

$$H(I) = -\sum_{i} p(i) \log p(i)$$

amount of information contained in image I

Joint entropy

$$H(I,J) = -\sum_{i} \sum_{j} p(i,j) \log p(i,j)$$

amount of information contained in the combined image I, J

Could be used for registration...

$$D_{JE}(I \circ T, J) = H(I \circ T, J)$$

(Dis)similarity Measures

Mutual information [Viola et al. 1995]

$$MI(I,J) = H(I) + H(J) - H(I,J)$$

describes how well one image can be explained by another image

This can be rewritten in terms of marginal and joint probabilities

$$MI(I,J) = \sum_i \sum_j p(i,j) \log \frac{p(i,j)}{p(i)\, p(j)}$$

The dissimilarity measure is then defined as

$$D_{MI}(I \circ T, J) = -MI(I \circ T, J)$$

(Dis)similarity Measures

Normalised mutual information [Studholme et al. 1999]

$$NMI(I,J) = \frac{H(I) + H(J)}{H(I,J)}$$

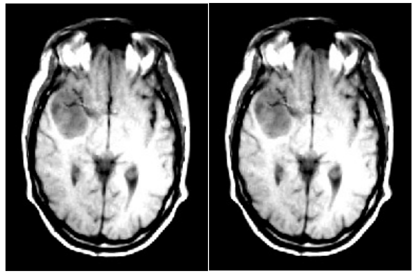
is independent of the amount of overlap between images

The dissimilarity measure is then defined as

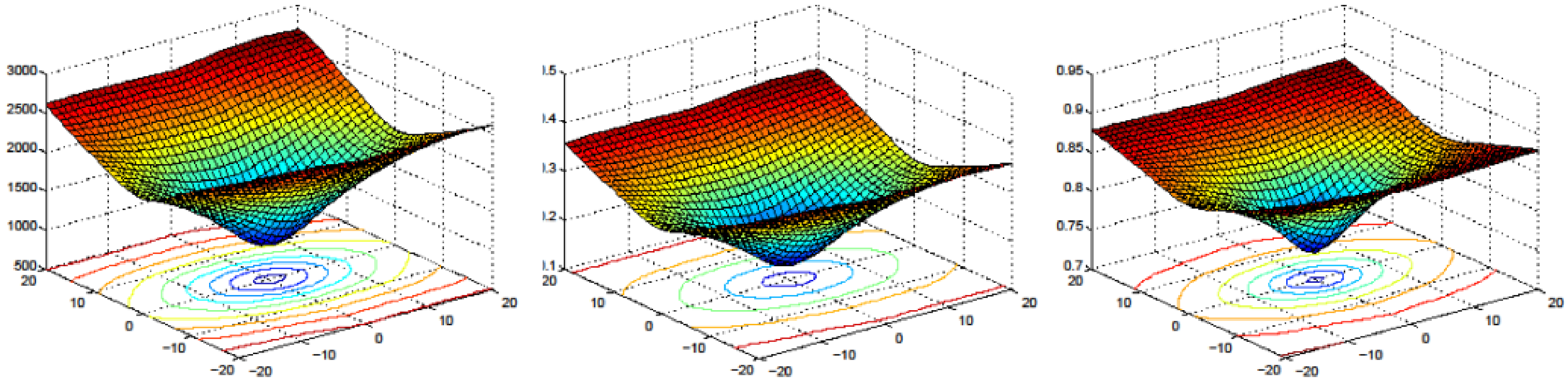
$$D_{NMI}(I \circ T, J) = -NMI(I \circ T, J)$$

Assumption: statistical relationship between intensity distributions
Application: (mainly) multi-modal registration (e.g. CT-MR)

(Dis)similarity Measures

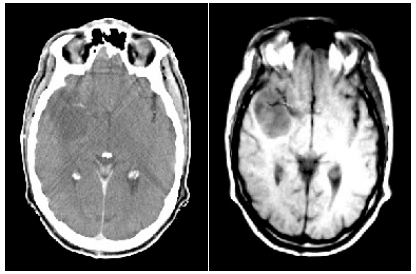


Translation experiment: mono-modal

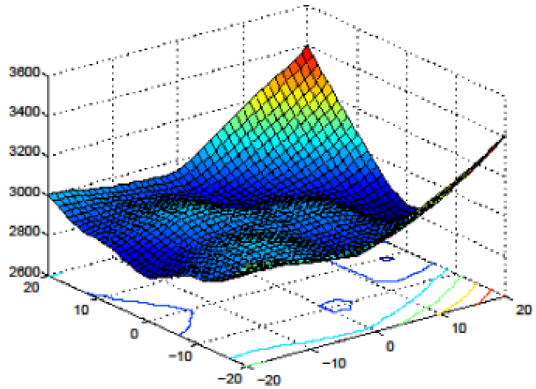


D_{SSD} D_{CC} D_{NMI}

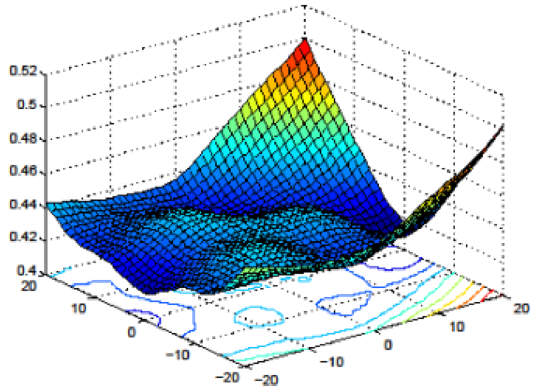
(Dis)similarity Measures



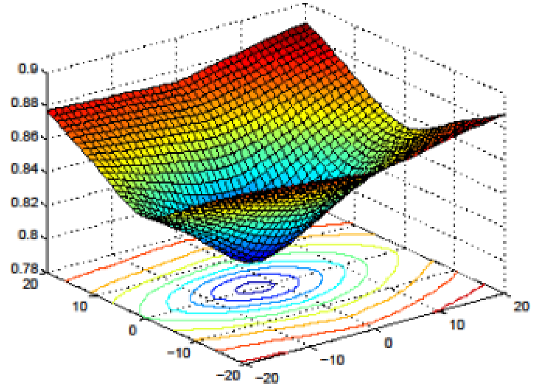
Translation experiment: multi-modal



D_{SSD}



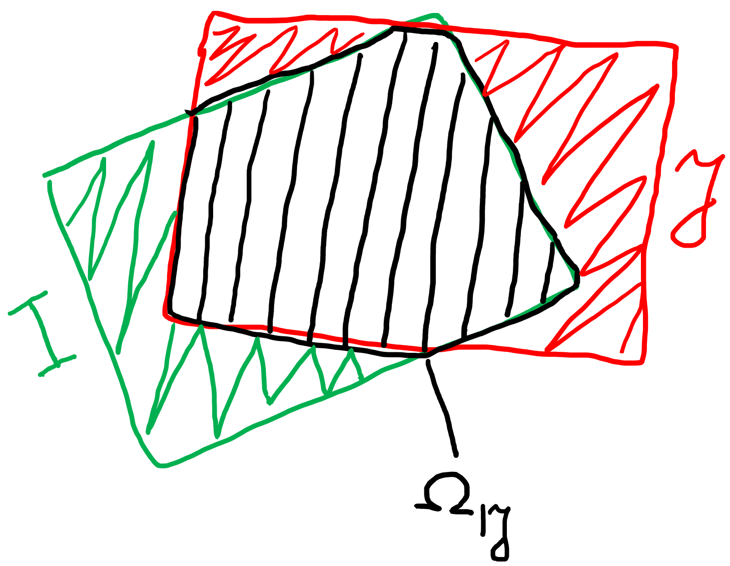
D_{CC}



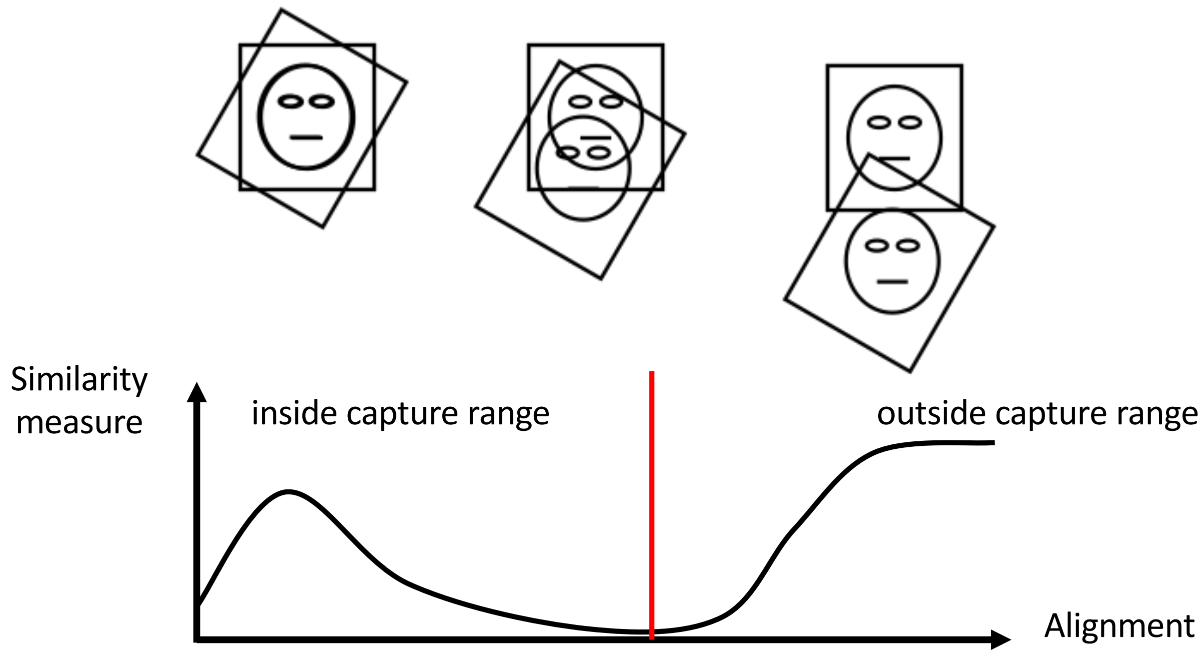
D_{NMI}

Image Overlap

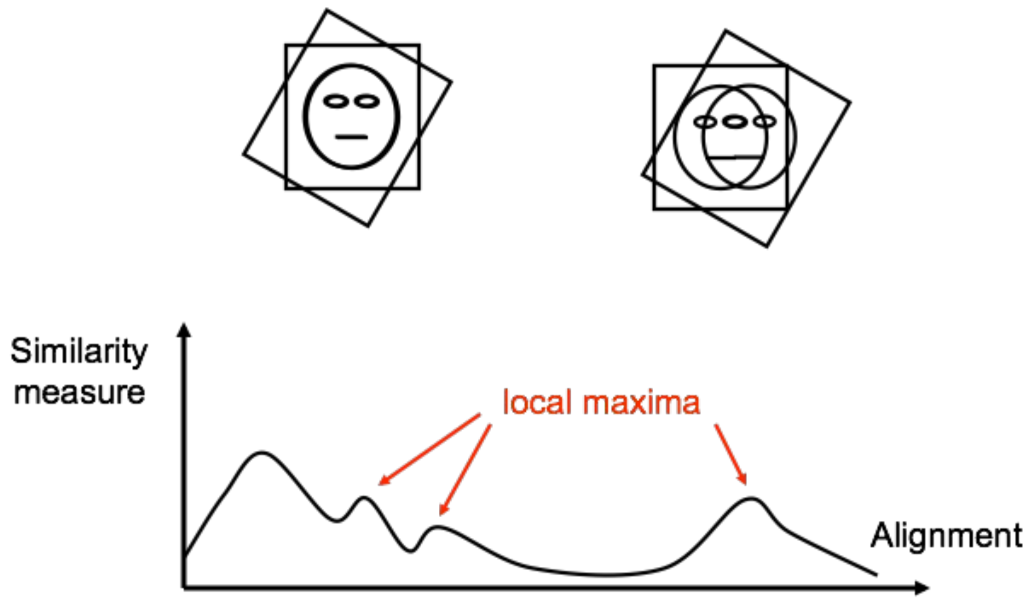
(Dis)similarity measures are evaluated in the overlapping region of the two images



Capture Range

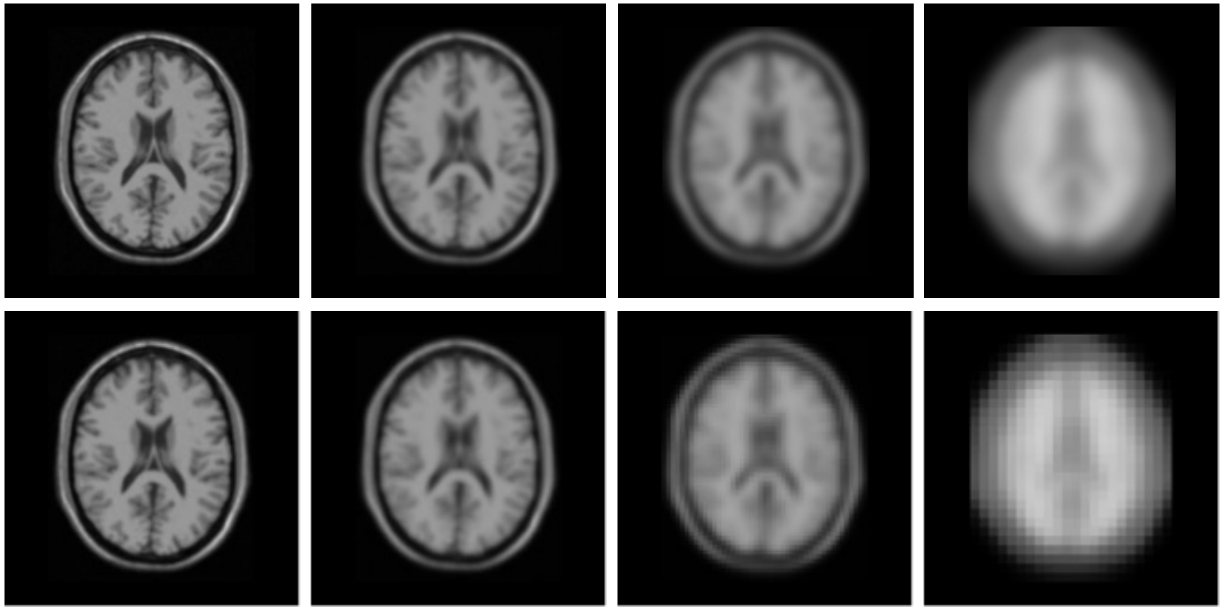


Local Optima



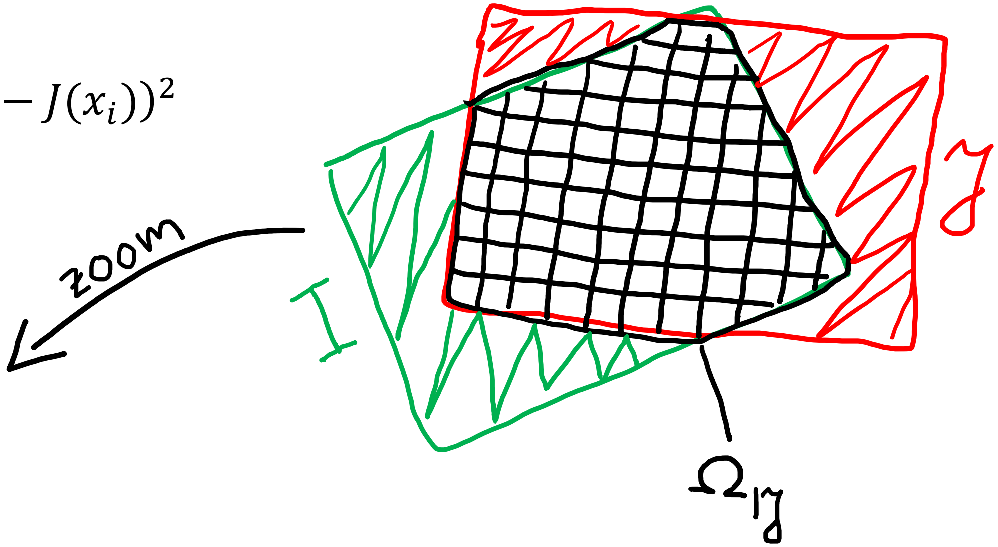
Multi-scale, hierarchical Registration

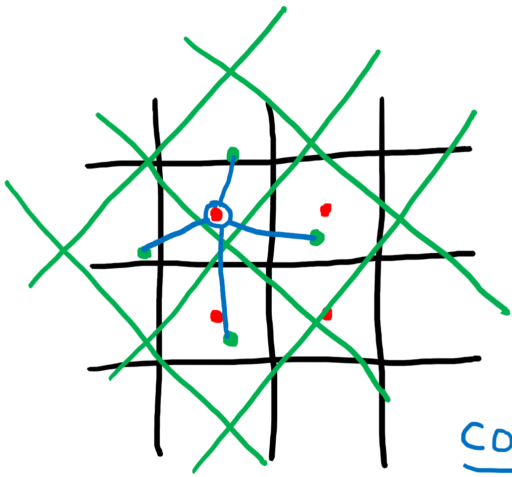
- Successively increase degrees of freedom
- Gaussian image pyramids



Interpolation

$$D_{SSD}(I \circ T, J) = \frac{1}{N} \sum_{i=1}^{N} (I(T(x_i)) - J(x_i))^2$$





compute weighted sum for $I(T(x_i))$

interpolation

Intensity-based Registration

Optimisation problem

$$\hat{T} = \arg\min_{T} C(T)$$

return
the argument
(not the value)

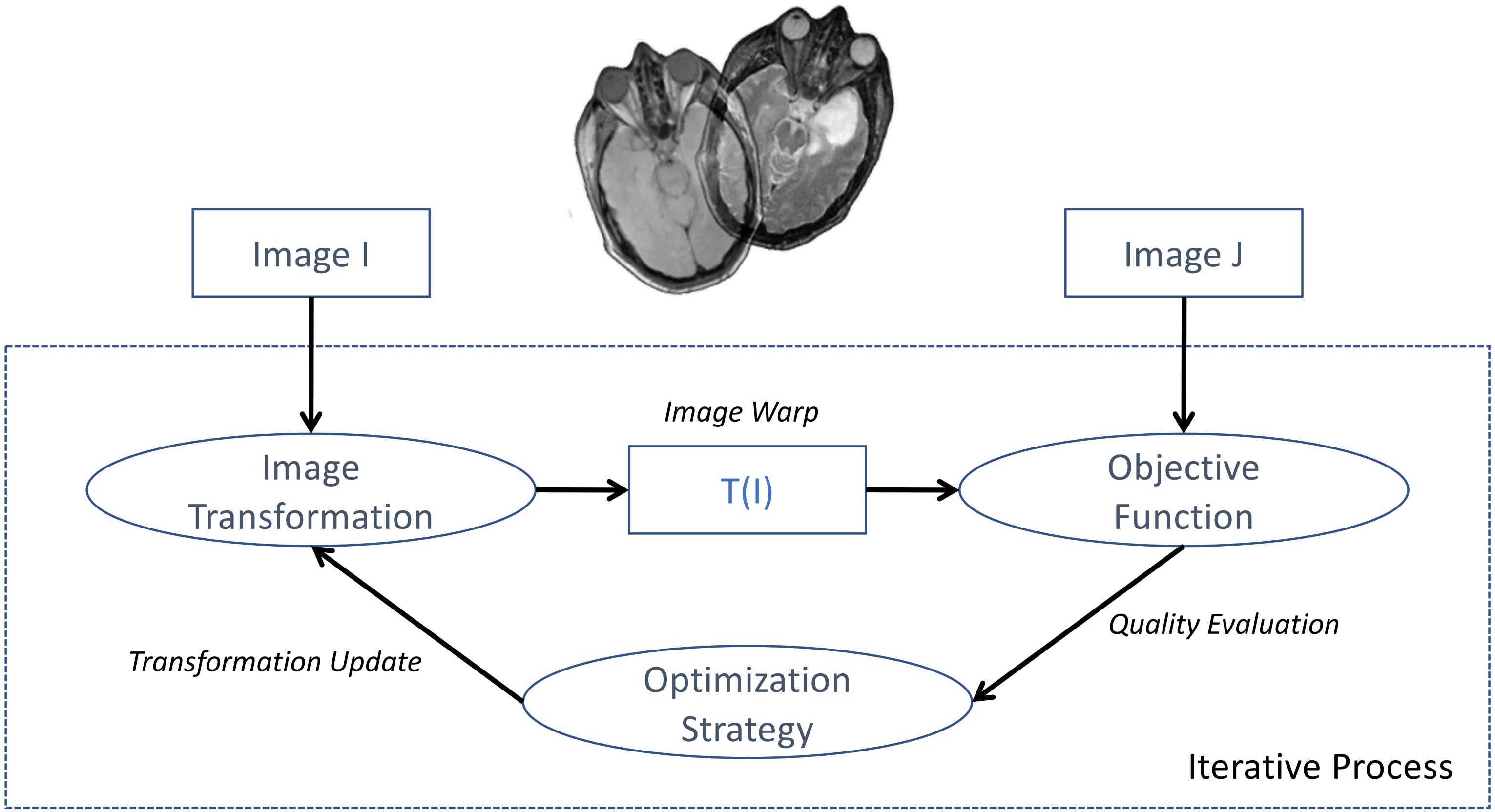
$\boxed{\text{search}}$ T
with minimum
cost value

?

cost function
$C : \mathbb{R}^{d} \to \mathbb{R}$

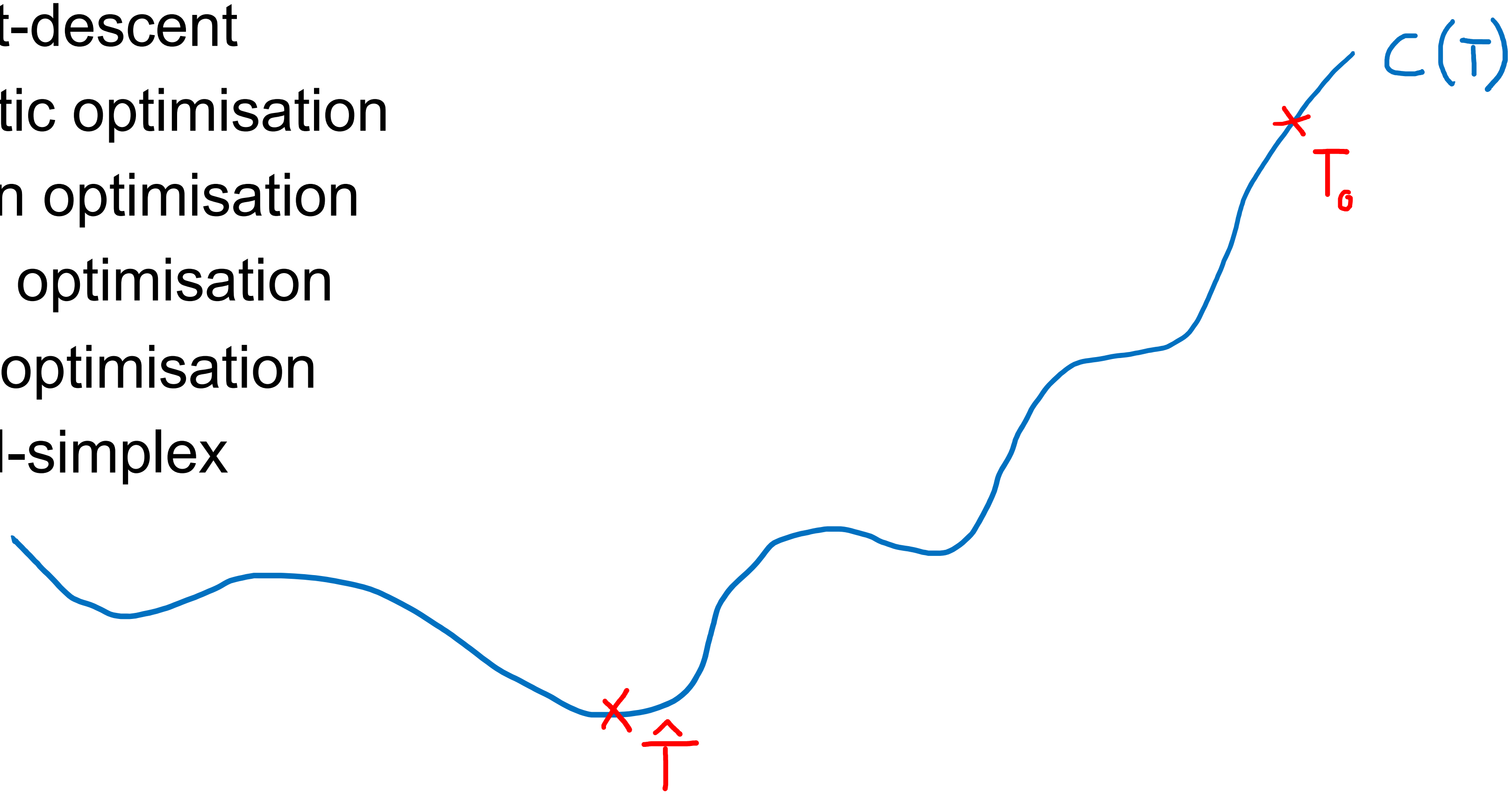
d.o.f./parameters
of transform

Registration as an Iterative Process



Optimisation Strategies

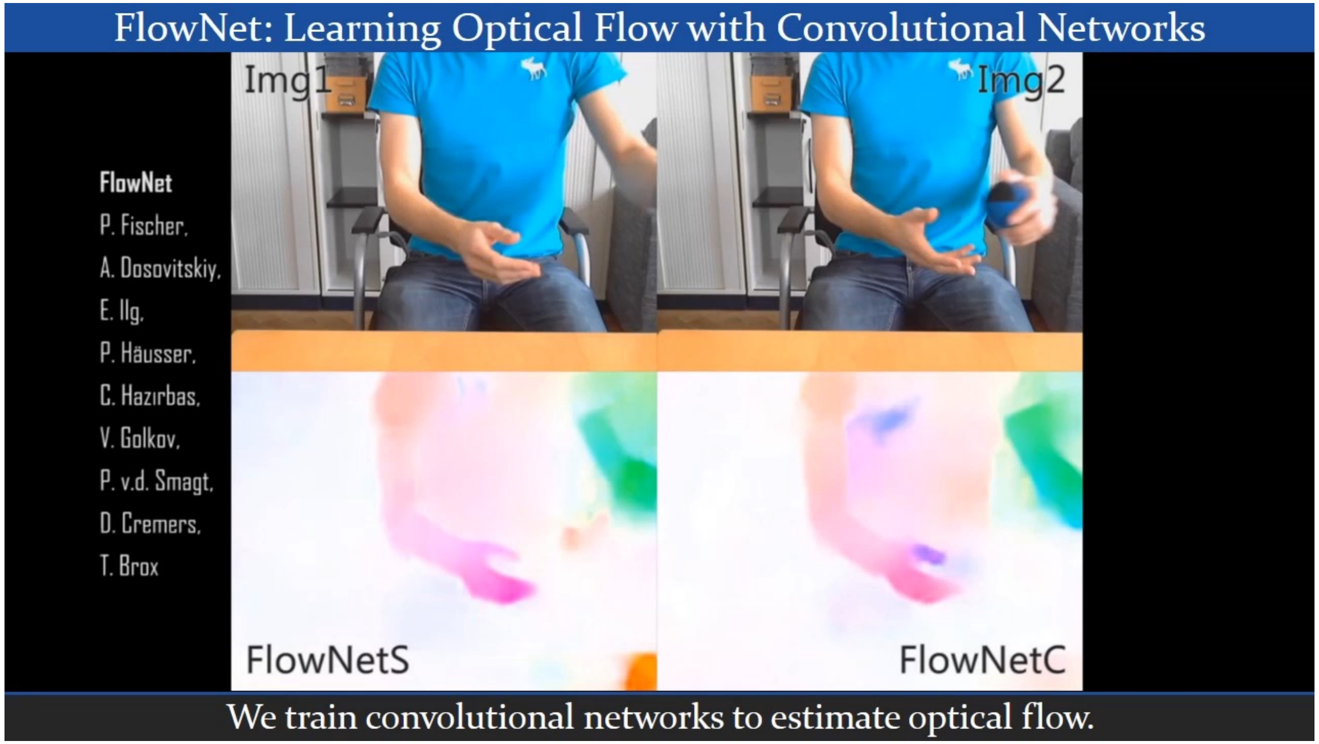
- Gradient-descent
- Stochastic optimisation
- Bayesian optimisation
- Discrete optimisation
- Convex optimisation
- Downhill-simplex
- …



Registration with Neural Networks

Supervised Learning Approaches

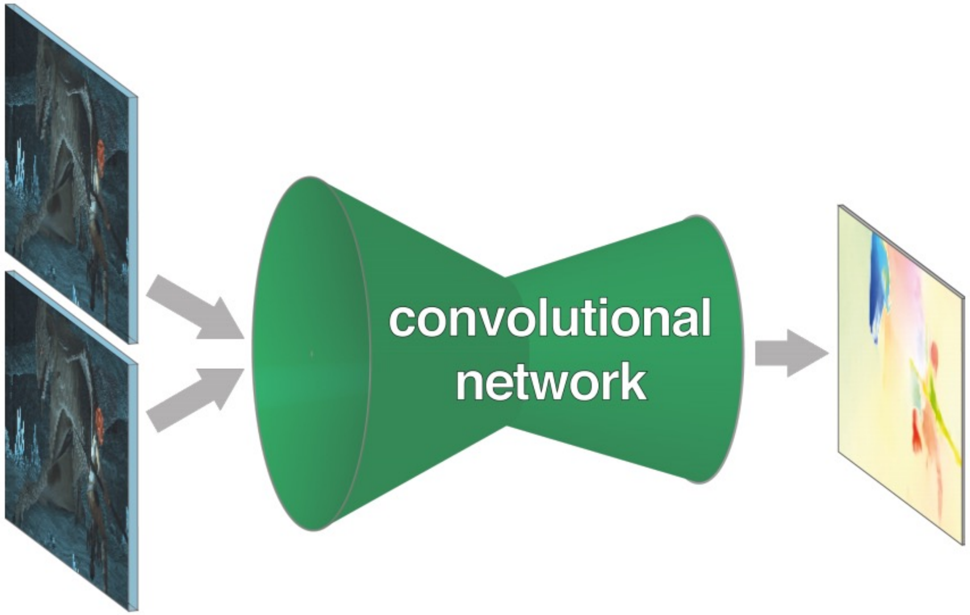
FlowNet: Learning Optical Flow with Convolutional Networks



https://arxiv.org/abs/1504.06852

Supervised Learning Approaches

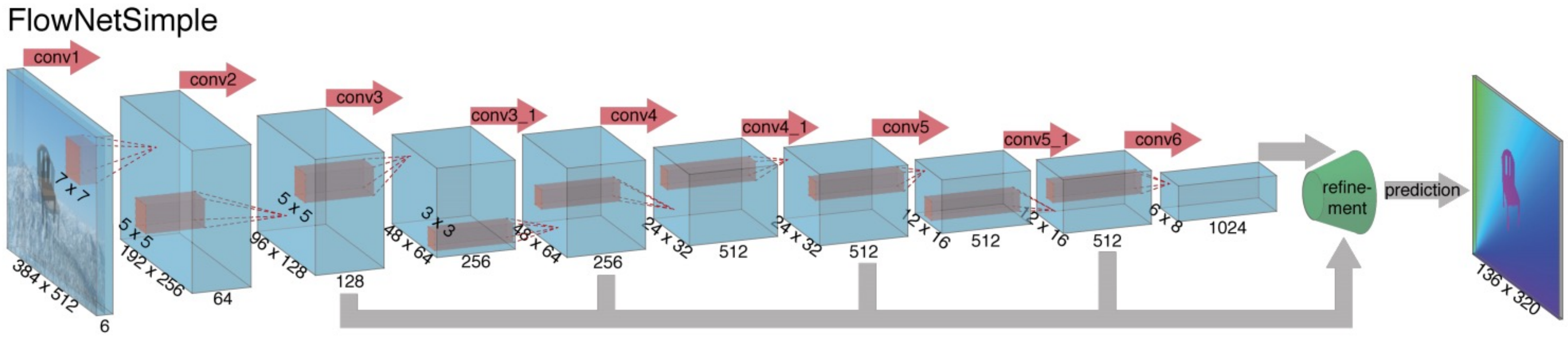
FlowNet: Learning Optical Flow with Convolutional Networks



https://arxiv.org/abs/1504.06852

Supervised Learning Approaches

FlowNet: Learning Optical Flow with Convolutional Networks



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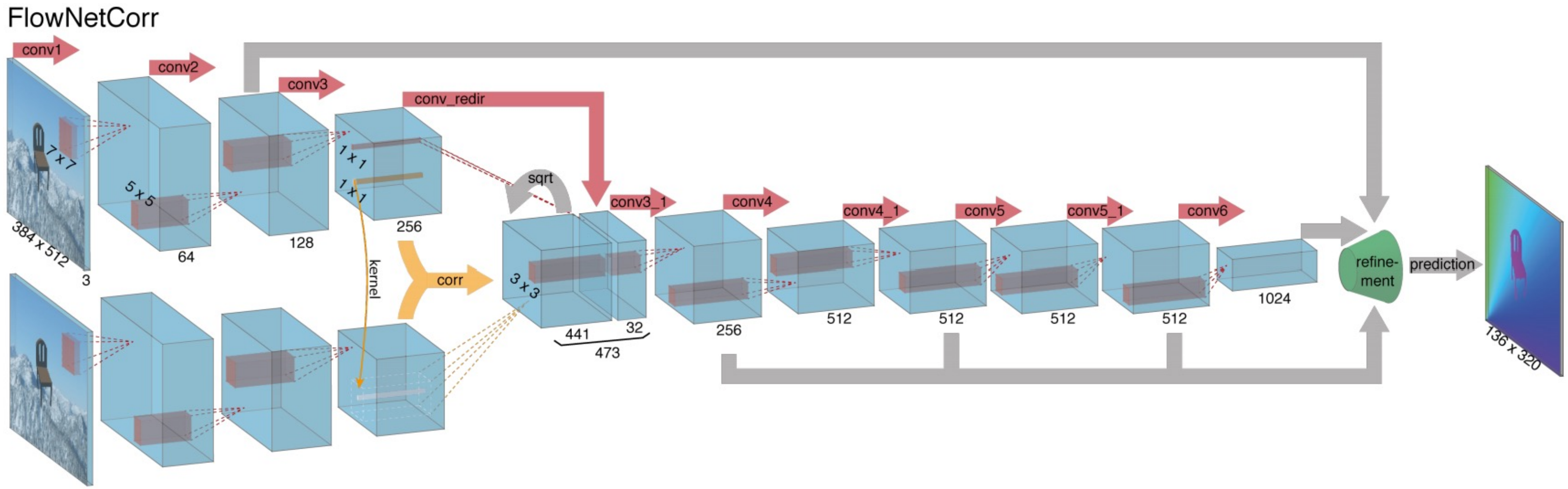
Supervised Learning Approaches

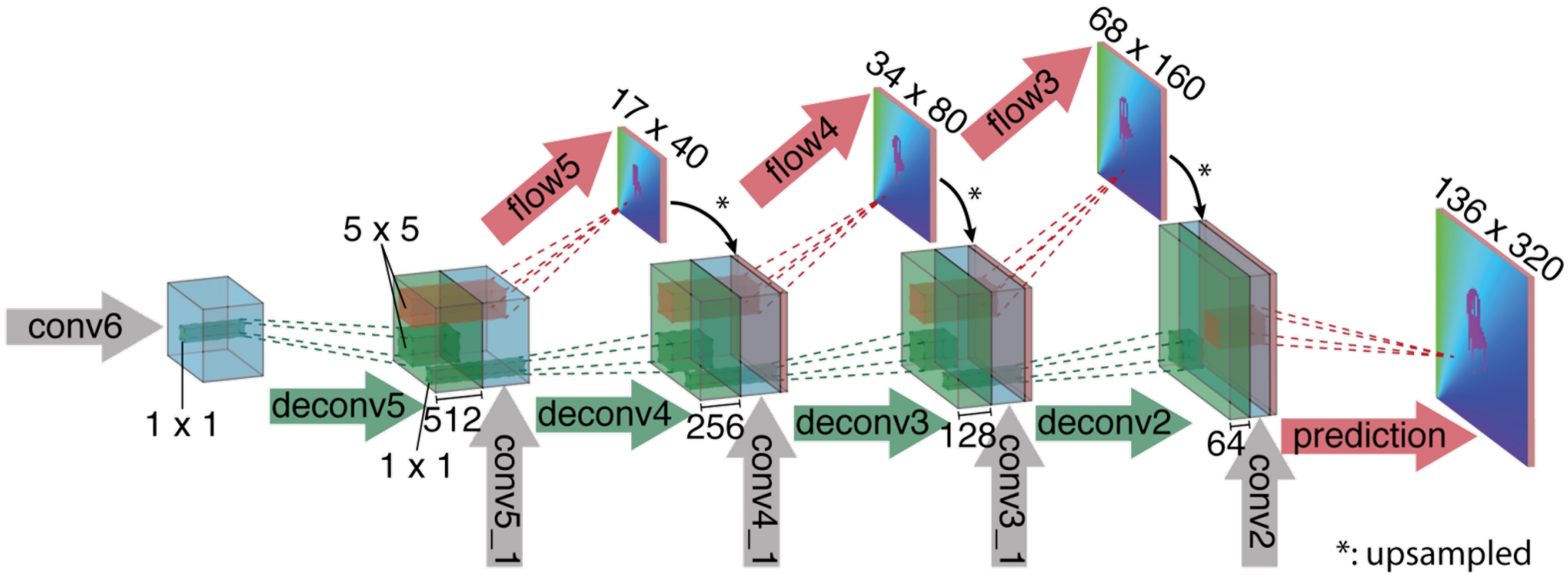
FlowNet: Learning Optical Flow with Convolutional Networks



https://arxiv.org/abs/1504.06852

Supervised Learning Approaches

FlowNet: Learning Optical Flow with Convolutional Networks



https://arxiv.org/abs/1504.06852

Supervised Learning Approaches

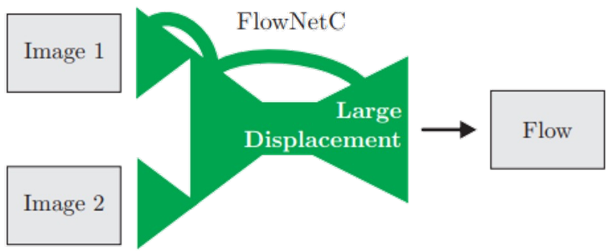
FlowNet: Learning Optical Flow with Convolutional Networks

Trained on “Flying Chairs” (plus fine-tuning)

https://arxiv.org/abs/1504.06852

Supervised Learning Approaches

FlowNet 2.0: Evolution of Optical Flow Estimation with Deep Networks



https://arxiv.org/abs/1612.01925

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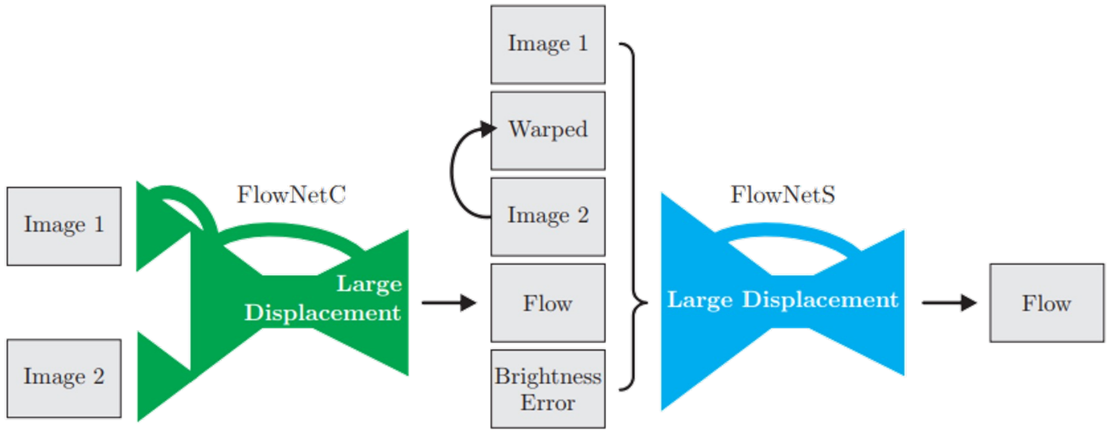

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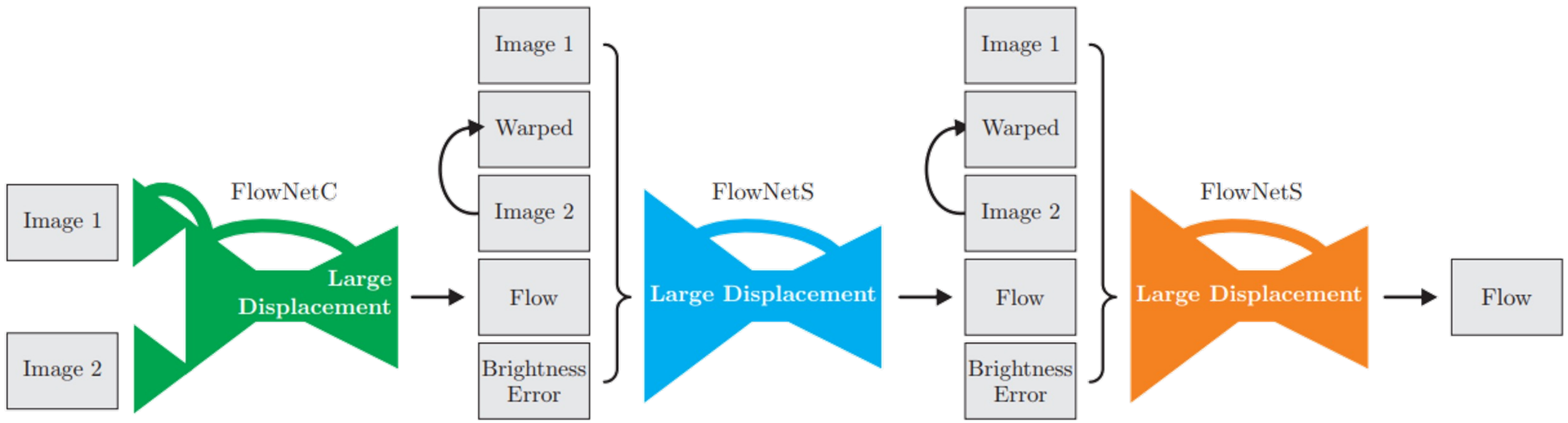

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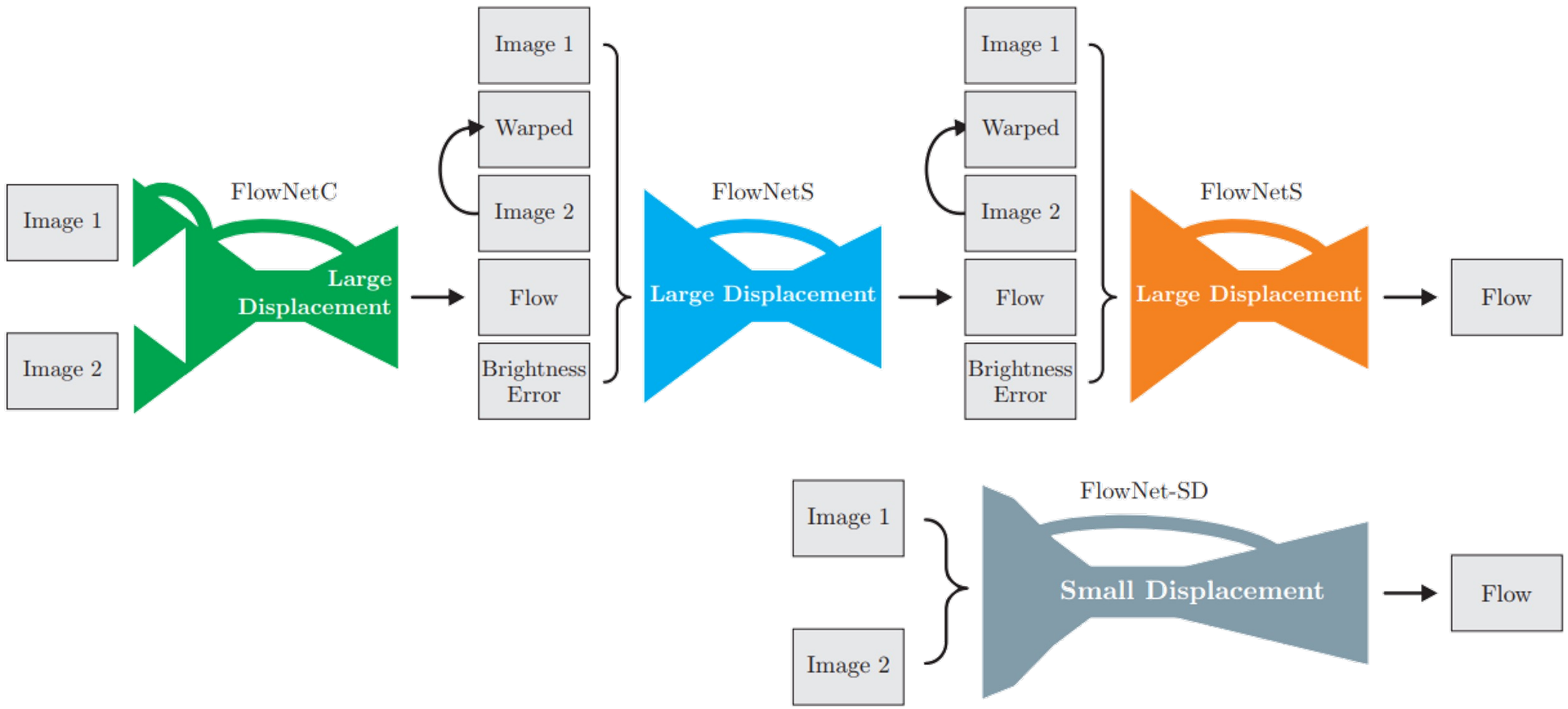

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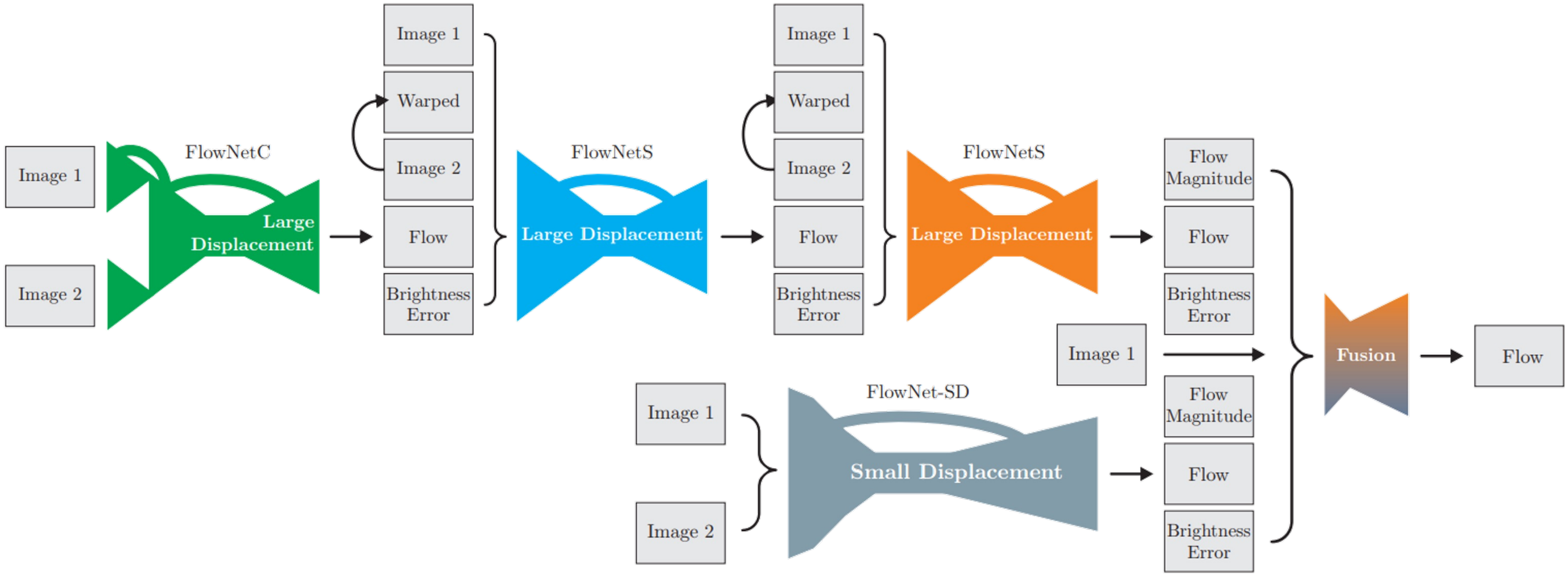

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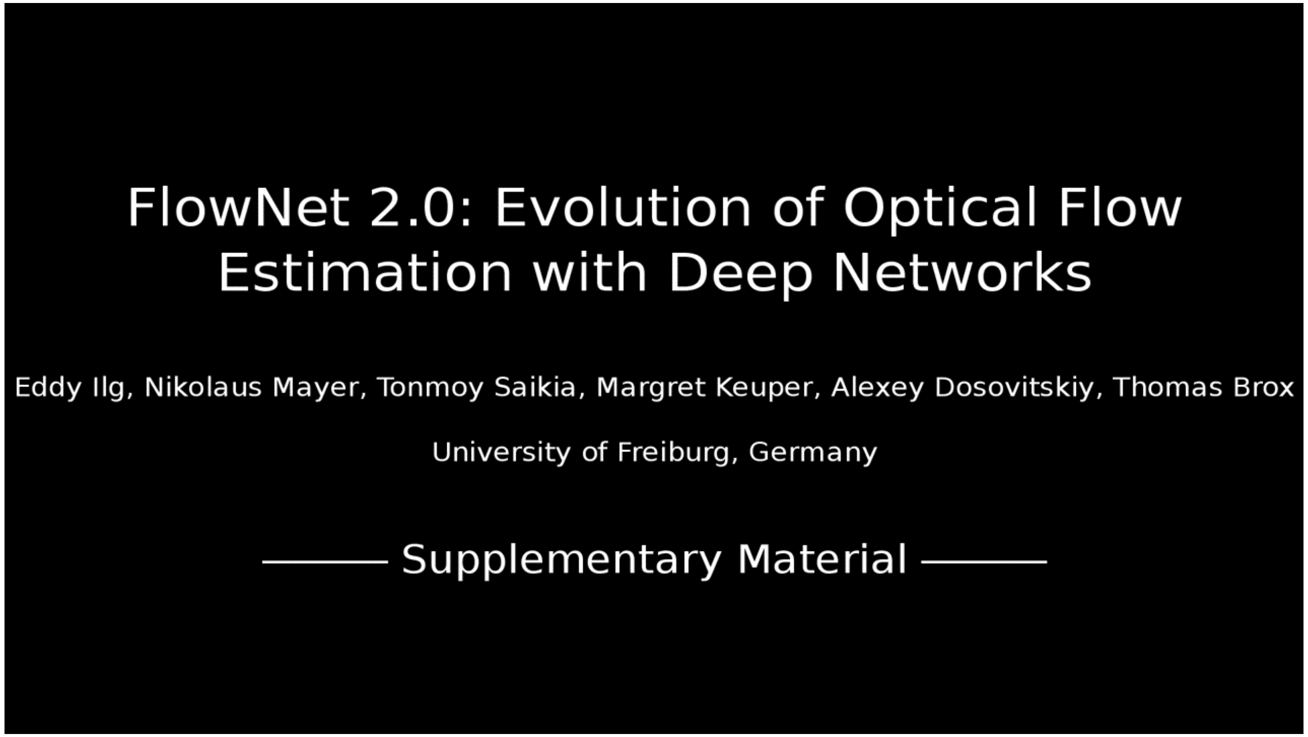

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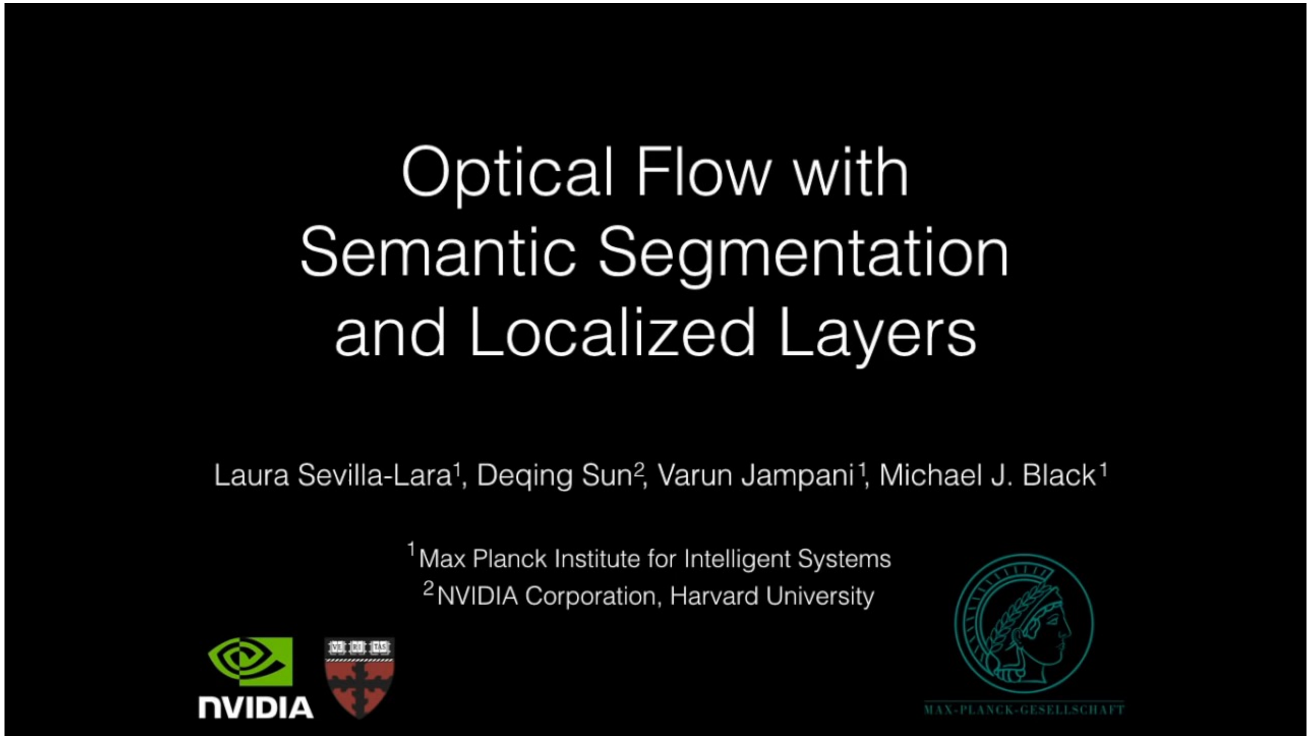
Supervised Learning Approaches

Optical Flow with Semantic Segmentation and Localized Layers

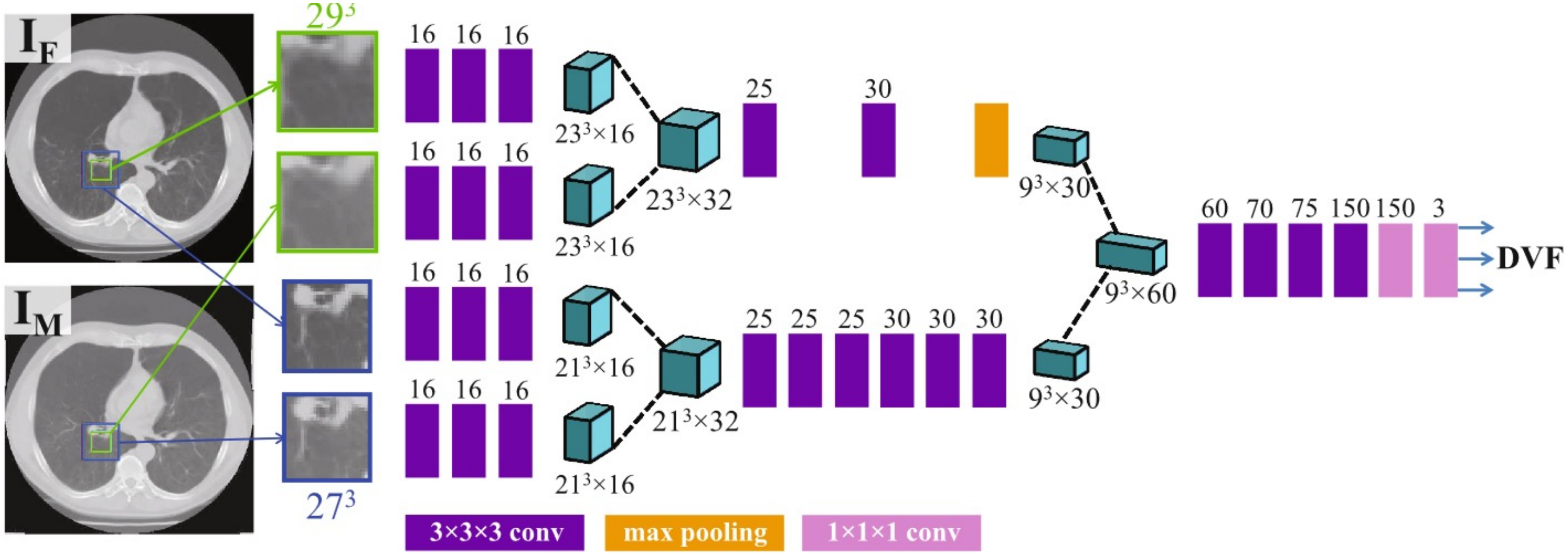


https://arxiv.org/abs/1603.03911

Supervised Learning Approaches

Nonrigid Image Registration Using Multi-scale 3D CNNs

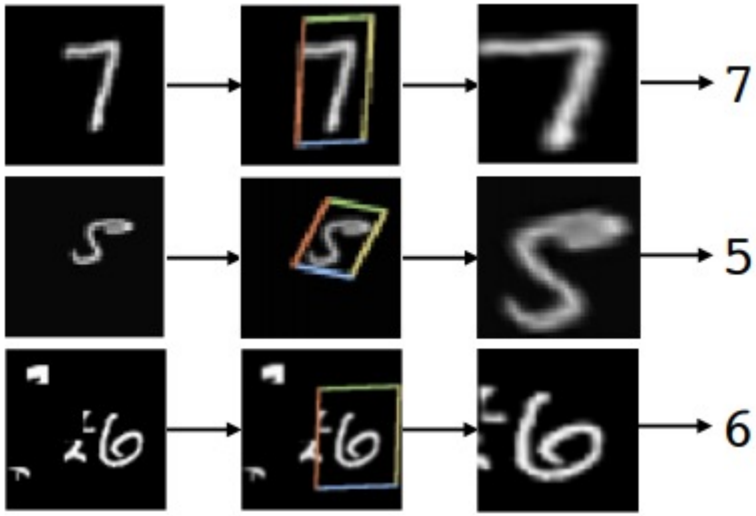
Trained on synthetic deformations

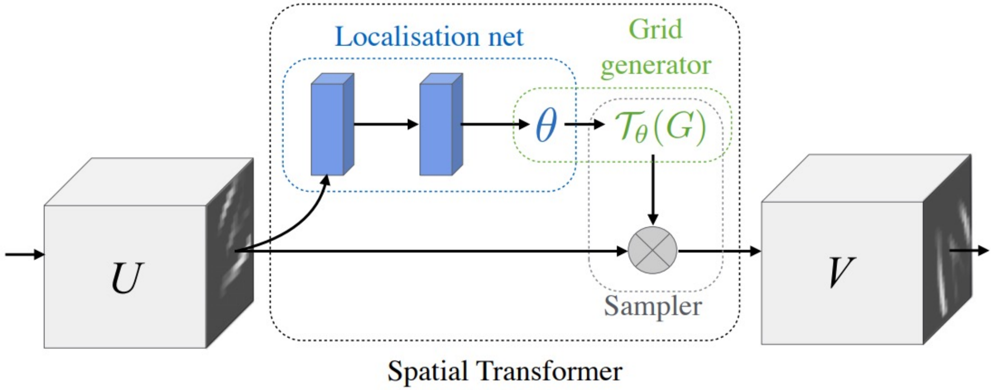


https://doi.org/10.1007/978-3-319-66182-7_27

Unsupervised Learning Approaches

Spatial Transformer Networks





PyTorch Tutorial
https://pytorch.org/tutorials/intermediate/spatial_transformer_tutorial.html

https://arxiv.org/abs/1506.02025

Unsupervised Learning Approaches

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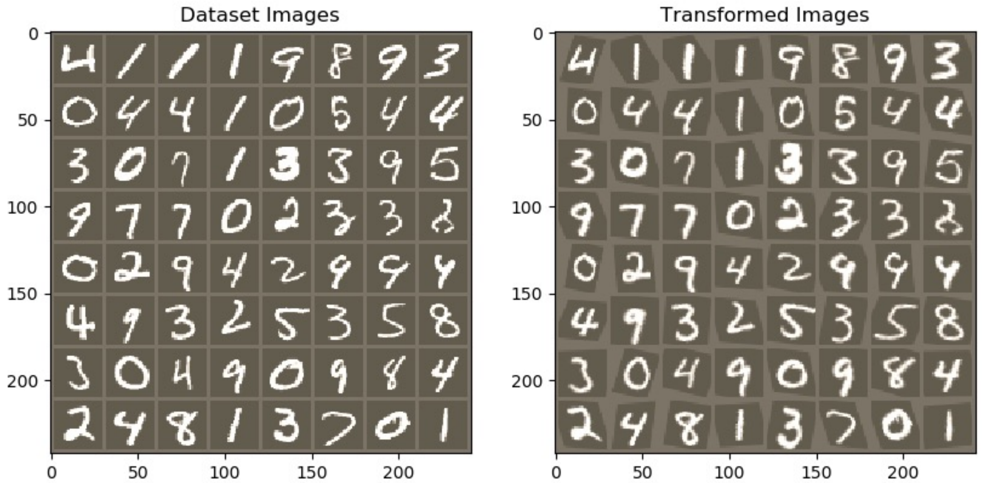
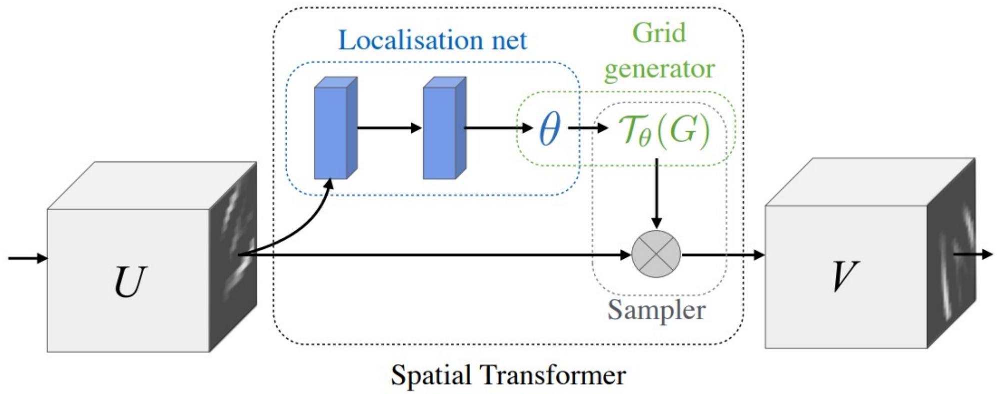


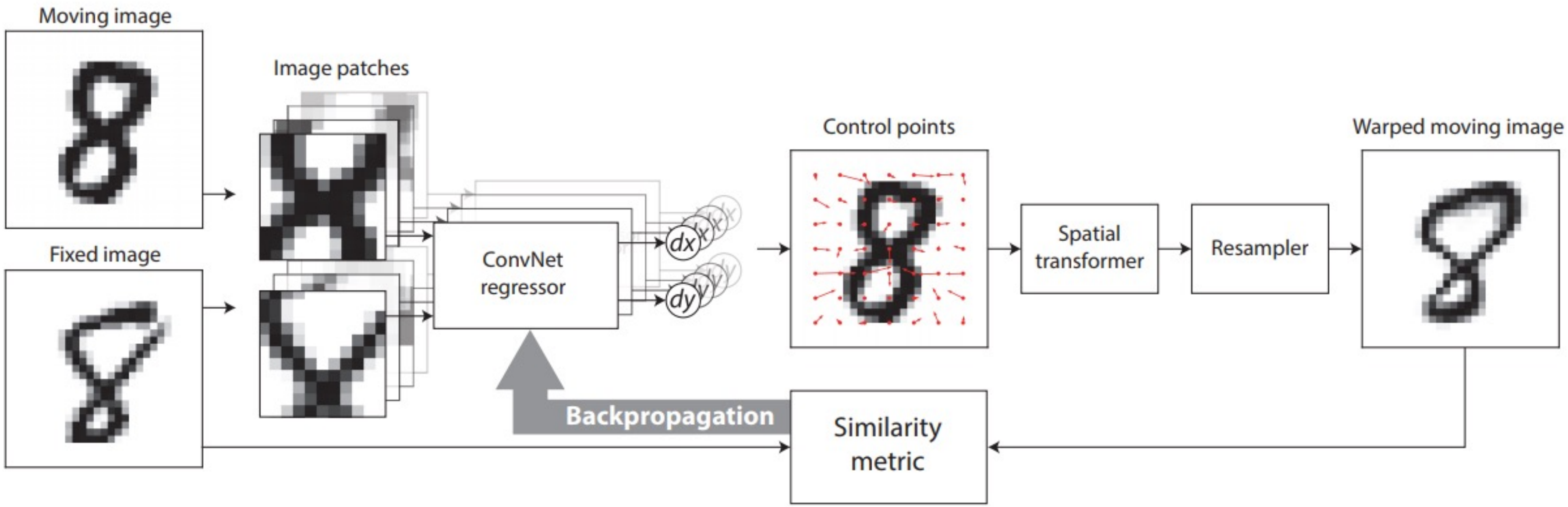
https://pytorch.org/tutorials/intermediate/spatial_transformer_tutorial.html



https://arxiv.org/abs/1506.02025

Unsupervised Learning Approaches

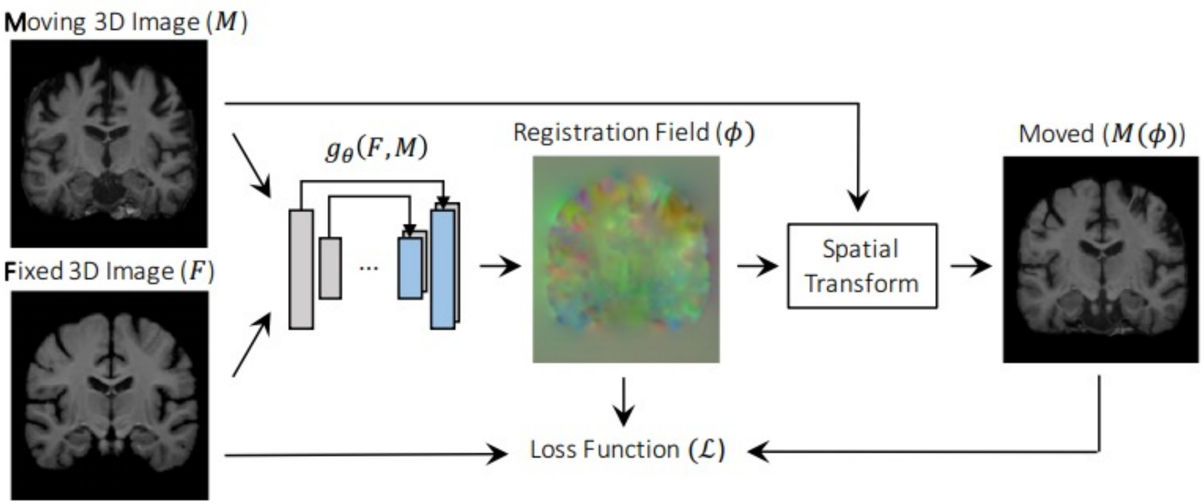
End-to-End Unsupervised Deformable Image Registration with a CNN

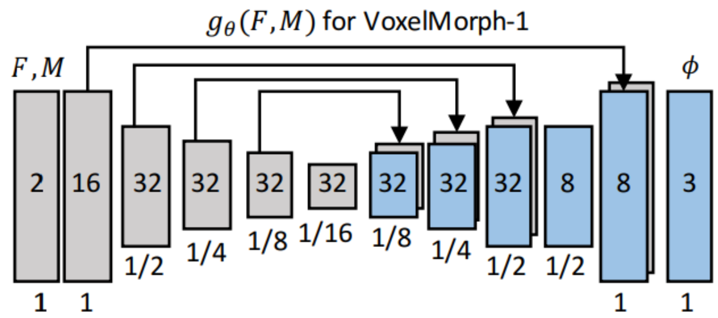


https://arxiv.org/abs/1704.06065

Unsupervised Learning Approaches

An Unsupervised Learning Model for Deformable Image Registration





https://arxiv.org/abs/1802.02604

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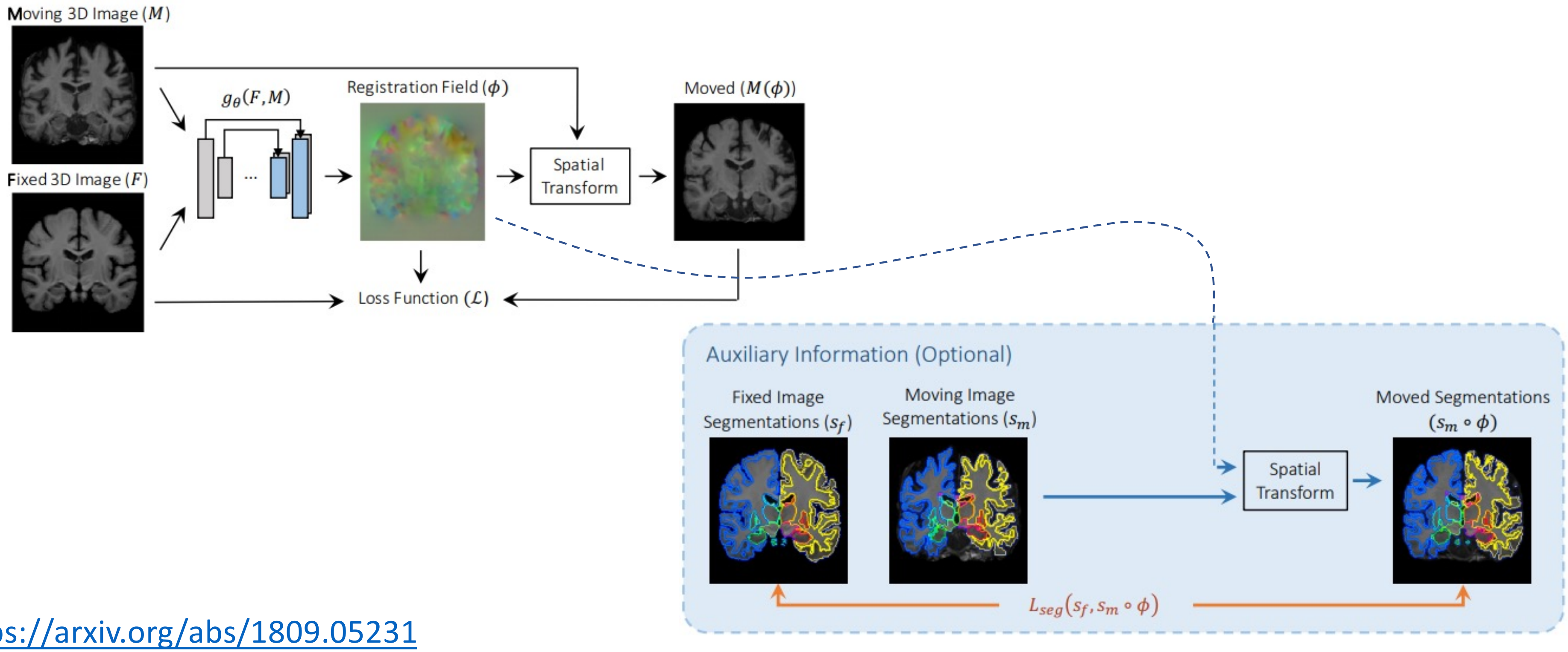
VoxelMorph: A Learning Framework for Deformable Image Registration



https://arxiv.org/abs/1809.05231

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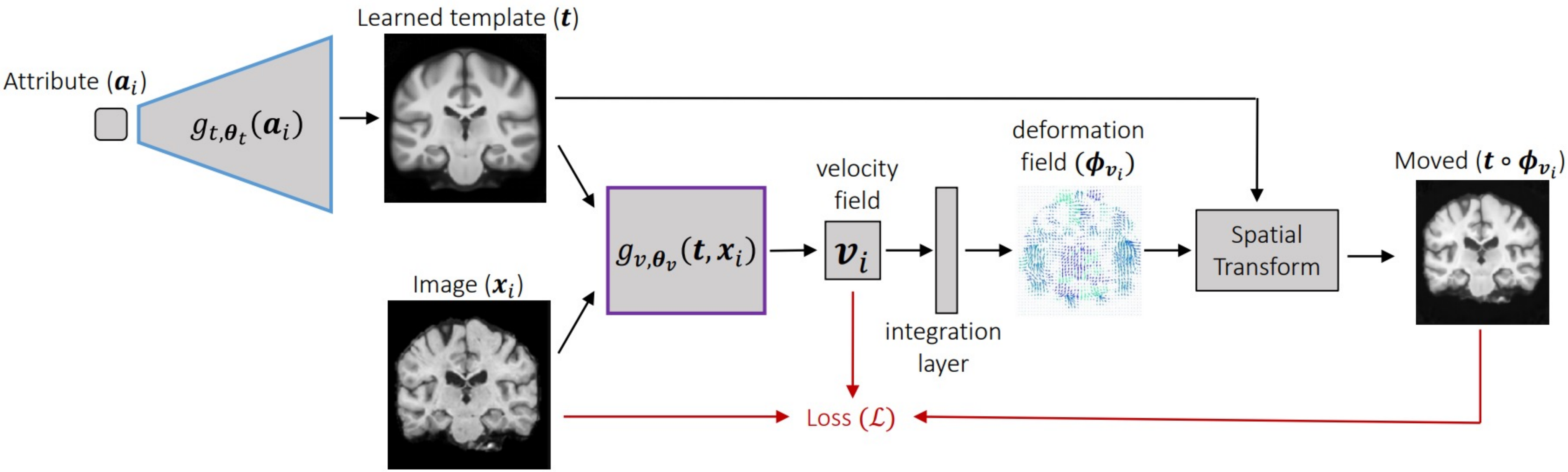
Learning Conditional Deformable Templates



https://arxiv.org/abs/1908.02738

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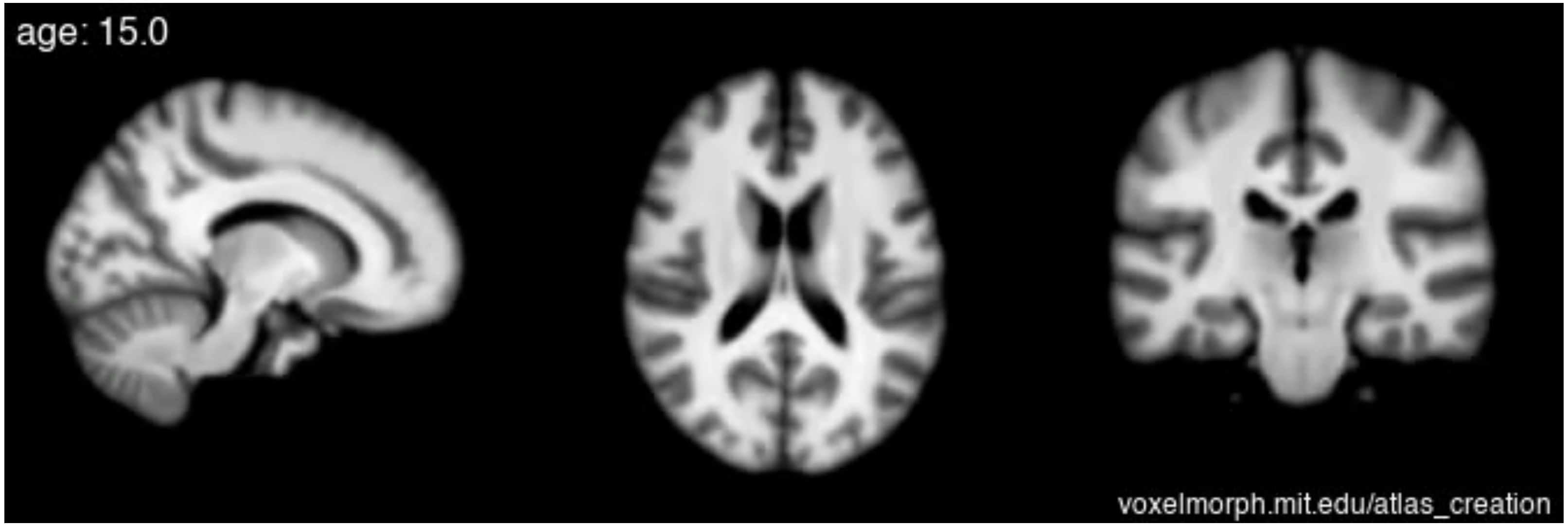
Learning Conditional Deformable Templates



https://arxiv.org/abs/1908.02738

Conclusion

Image registration with neural networks is an active field of research

1) Learning image representations that are optimal for registration

2) Learning to spatially normalise inputs for downstream prediction tasks