ICCR 2024
XX[th] International Conference on the use of Computers in Radiation therapy

UCL

Is Learning Based Image Registration Really the Future?

Jamie McClelland

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Wellcome/EPSRC centre Interventional and Surgical Science (WEISS)

Dept. Medical Physics and Biomedical Engineering

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Medical Image Registration: Past, Present, and Future…

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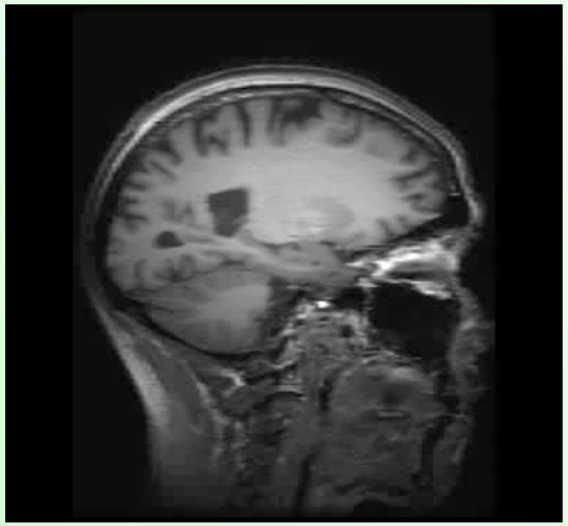
Overview

- Past: Classical image registration
- Present: Learning-based image registration
- Future: ???

What is Image Registration?

- Process of finding a spatial transformation that optimally aligns image A to image B
  - Image A called Source (or floating or moving) image
  - Image B called Target (or reference or fixed) image



MRI Target image (B)
PET Source image (A)

What is Image Registration?

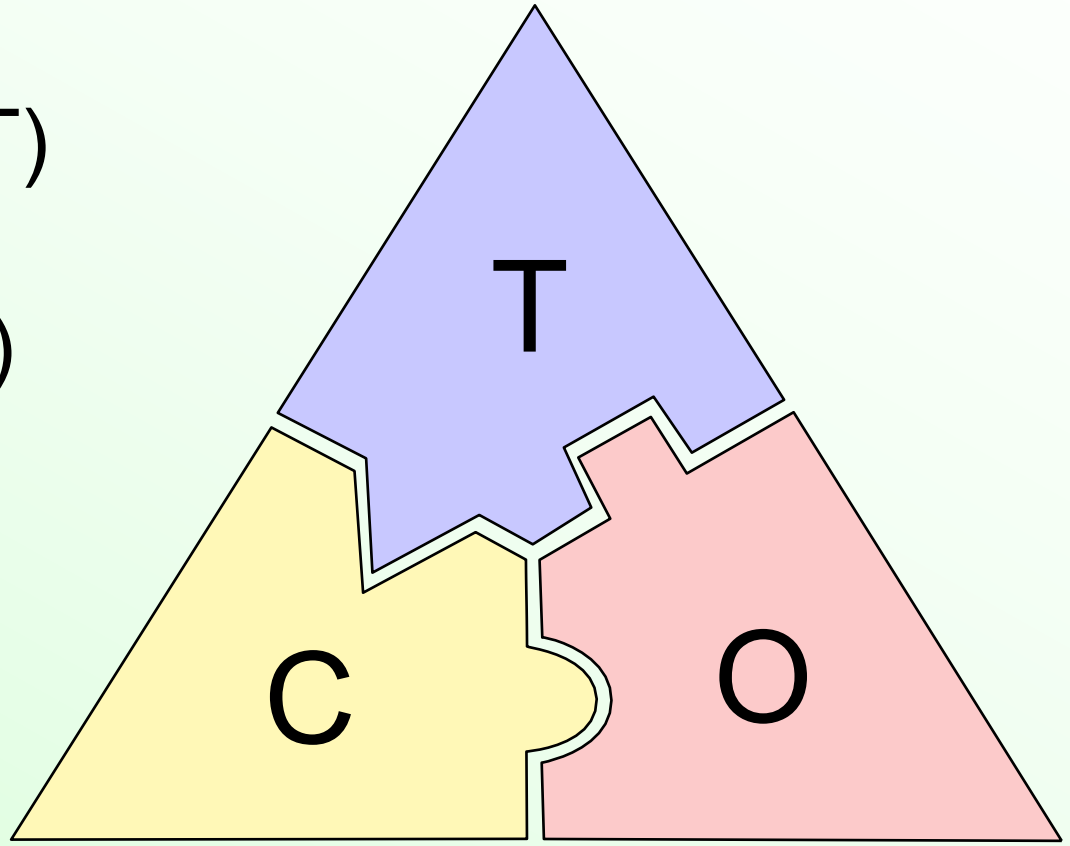
- What do we mean by ‘aligned?’
  - Establishing correspondence
  - Not always obvious what ‘correct’ correspondence is
    - Image contain different information,
      - e.g. MRI and PET
    - Anatomy has changed between images,
      - e.g. before and after surgery
    - Images are from different subjects

Components of a registration algorithm

Transformation (T)

Cost Function (C)

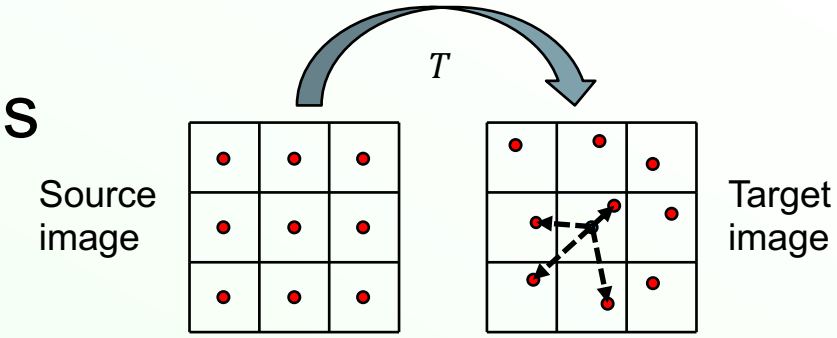
Optimiser (O)



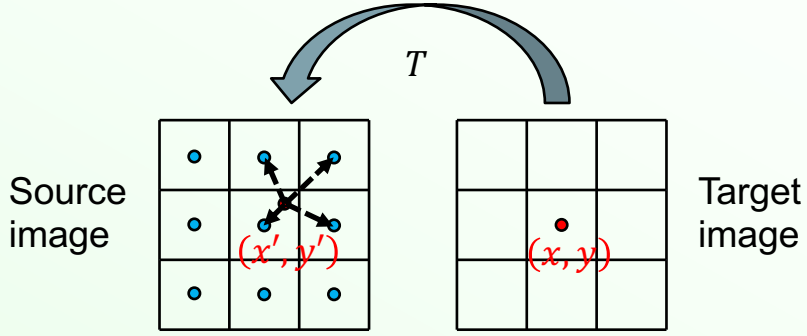
What is a transformation?

- Spatial mapping between coordinate systems

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



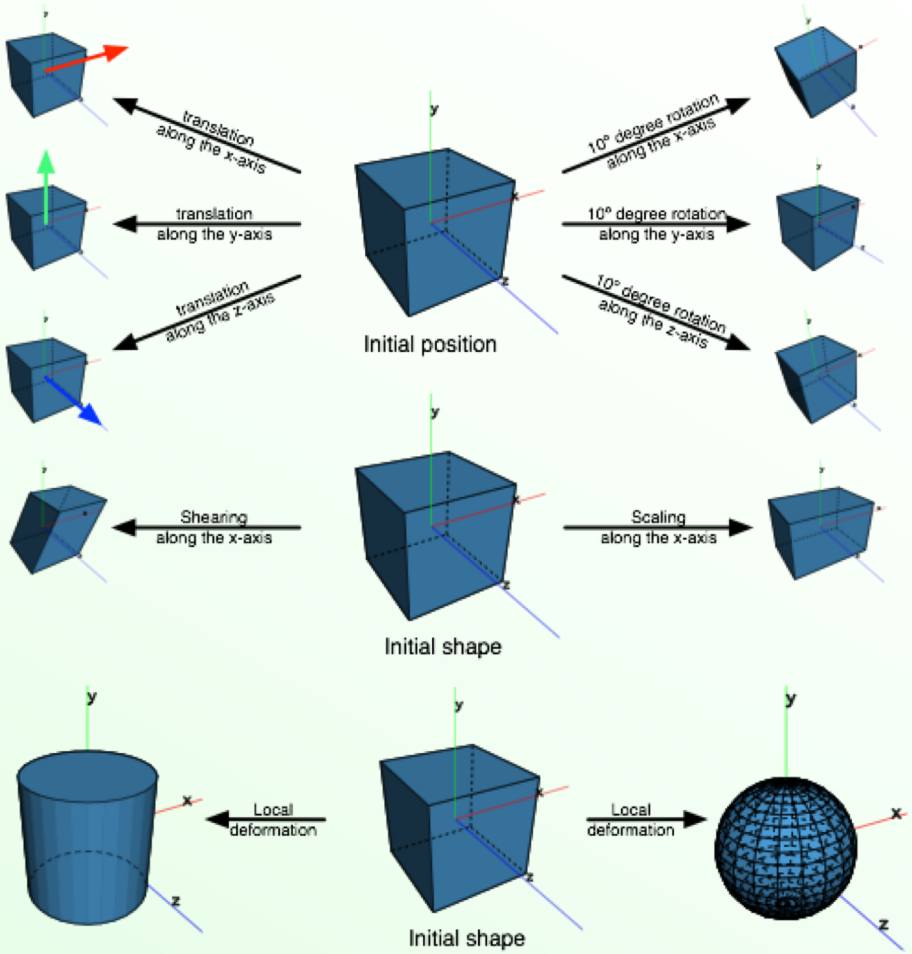
- Used to resample (warp) the source image into the space of the target image
  - Requires interpolation
  - Transformation usually maps from target to source image



- Does NOT necessarily represent physical changes between images

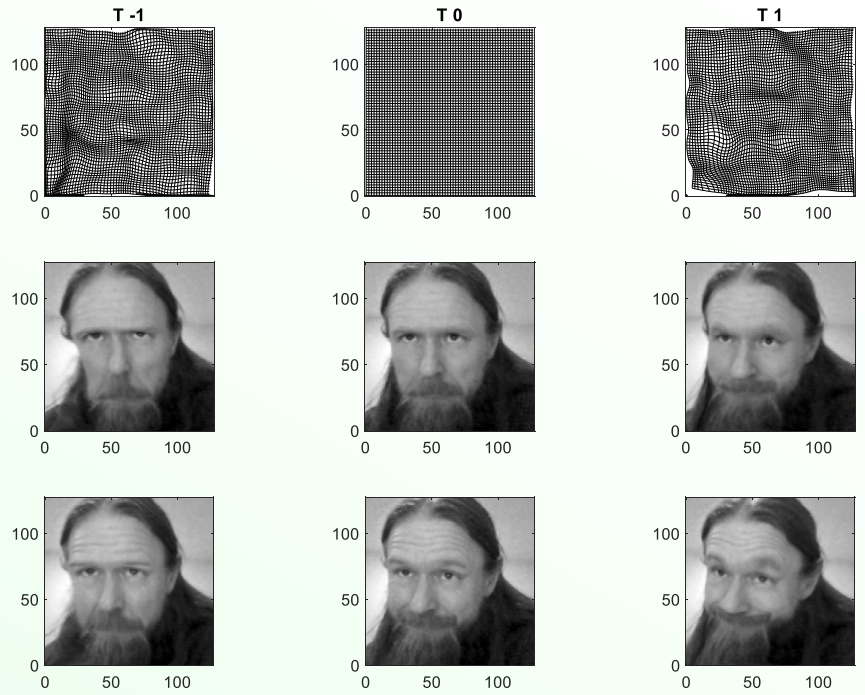
Types of transformation

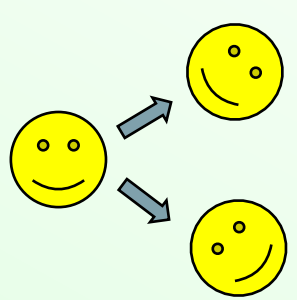
- Rigid
  - Translation, rotation
- Affine
  - Rigid, shearing, scaling
- Deformable (non-rigid, non-linear)
  - Free-form deformations
  - ‘Non-parametric’ (voxel-based)
  - Velocity fields
    - Often used for diffeomorphic transformations
- 2D-2D, 3D-3D, 4D-4D, 3D-4D, 2D-3D,…



What is a diffeomorphism?

- One-to-one mapping (bijective)
  - Transformation has an inverse
  - No folding
- Transformation and inverse are differentiable
  - No discontinuities
- Nice mathematical properties
  - Topology is preserved
    - Structures preserved
  - Composing diffeomorphisms gives a diffeomorphism
  - Statistics on velocity fields (Log-Euclidean framework)



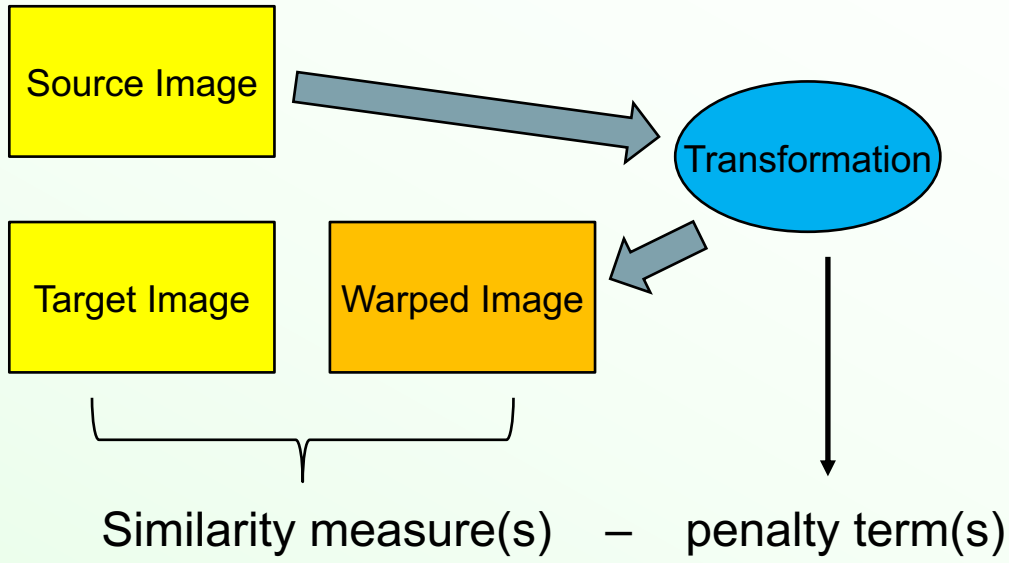


Mean of deformation fields

Mean of velocity fields

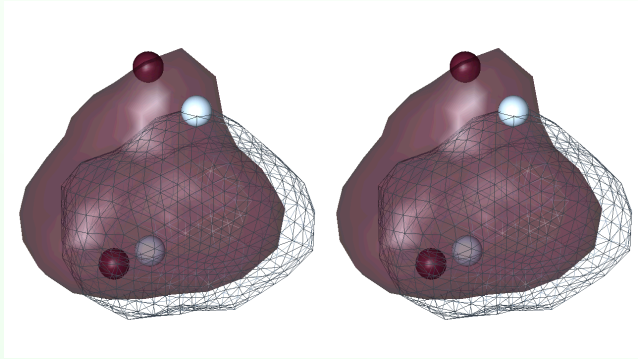
What is a cost function?

- Used to measure how good the registration result is
- Composed of two parts:
  - One or more similarity measures
    - Function of target image and warped source image
    - Choice will depend on type of images being registered
  - Zero or more penalty (constraint) terms
    - Function of transformation parameters
    - Penalises undesirable transformations
      - Encourages plausible/~~realistic~~ transformations.
    - Different terms used depending on what is considered desirable behaviour
  - Often only one similarity measure and zero-to-two penalty terms are used

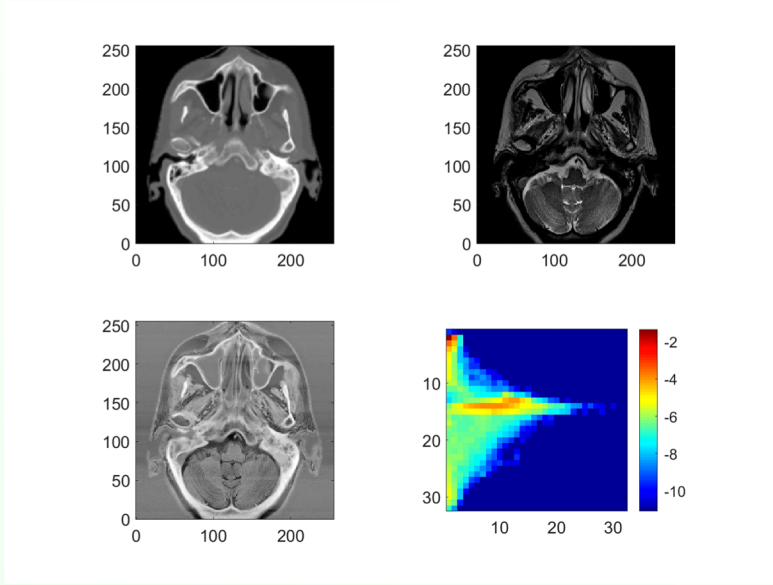


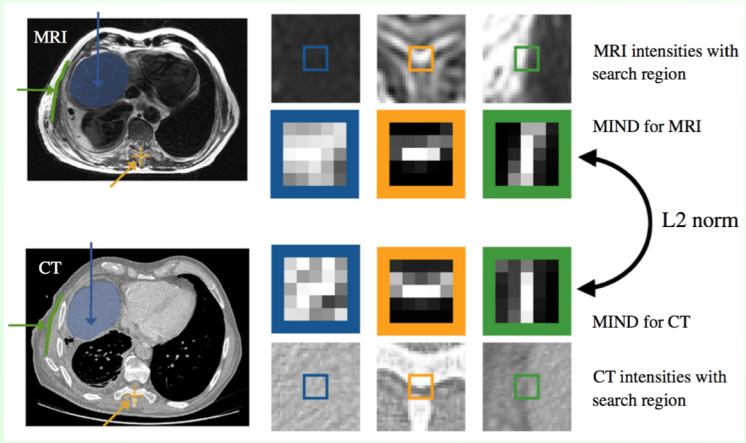
Similarity measures

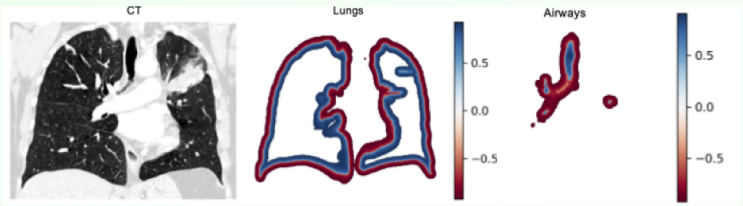
- Point/surface based



- Voxel-wise
  - SSD, MSD, NCC, MI, NMI,…
  - Locally normalised
    - LNCC, LNMI
  - Feature/structure based
    - MIND, distance maps







- Hybrid

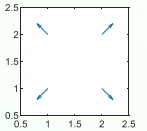
Penalty terms

- Using 1st order derivative
  - Diffusion (L2 norm), Linear energy,
  - L1 norm
  - Log of Jacobian Determinant

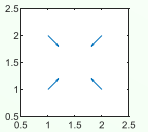
$$\mathrm{Jac}\left(T(\vec{x}_n)\right) = \begin{bmatrix} \frac{\partial T_1(\vec{x}_n)}{\partial x_1} & \cdots & \frac{\partial T_1(\vec{x}_n)}{\partial x_{N_{dim}}} \\ \vdots & \ddots & \vdots \\ \frac{\partial T_{N_{dim}}(\vec{x}_n)}{\partial x_1} & \cdots & \frac{\partial T_{N_{dim}}(\vec{x}_n)}{\partial x_{N_{dim}}} \end{bmatrix}$$

- Using 2nd order derivative
  - Bending energy

$$\left|\mathrm{Jac}\left(T(\vec{x}_n)\right)\right| > 1$$

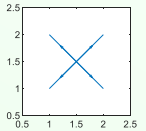


$$1 > \left|\mathrm{Jac}\left(T(\vec{x}_n)\right)\right| > 0$$



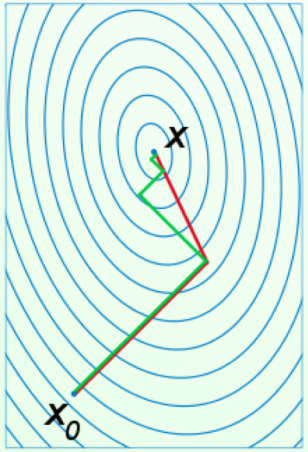
- Encourage transformations to be:
  - Smooth / piece-wise smooth / volume preserving

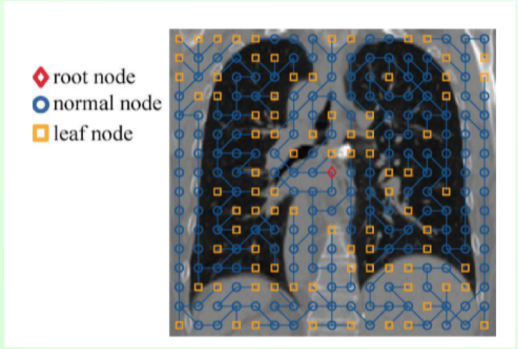
$$\left|\mathrm{Jac}\left(T(\vec{x}_n)\right)\right| \leq 0$$



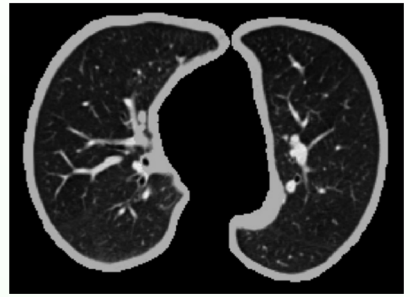
Optimisation

- Optimisation methods:
  - Gradient based methods
    - Gradient descent/ascent
    - Conjugate gradient
    - Other gradient based methods
  - Variational calculus
    - Partial differential equations
  - Discrete methods
    - Graph based





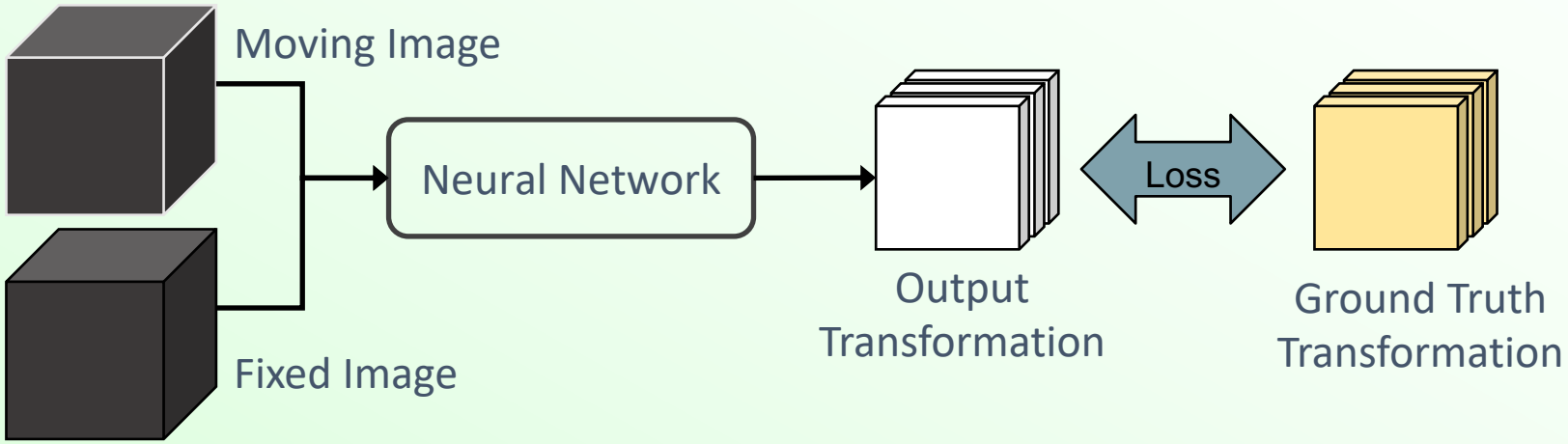
- Approaches/strategies
  - Multi-resolution
  - Cropping and masking images
  - Symmetric registration
  - Inverse-consistent registrations
  - Group-wise registrations



Learning based registrations

- Almost all current research on learning-based registrations
- Learn relationship between images and transformations from training data
  - Can calculate transformation very quickly for new images
  - Requires lots of images and computing resources for training
- Training can be:
  - Supervised, self-supervised, weakly supervised

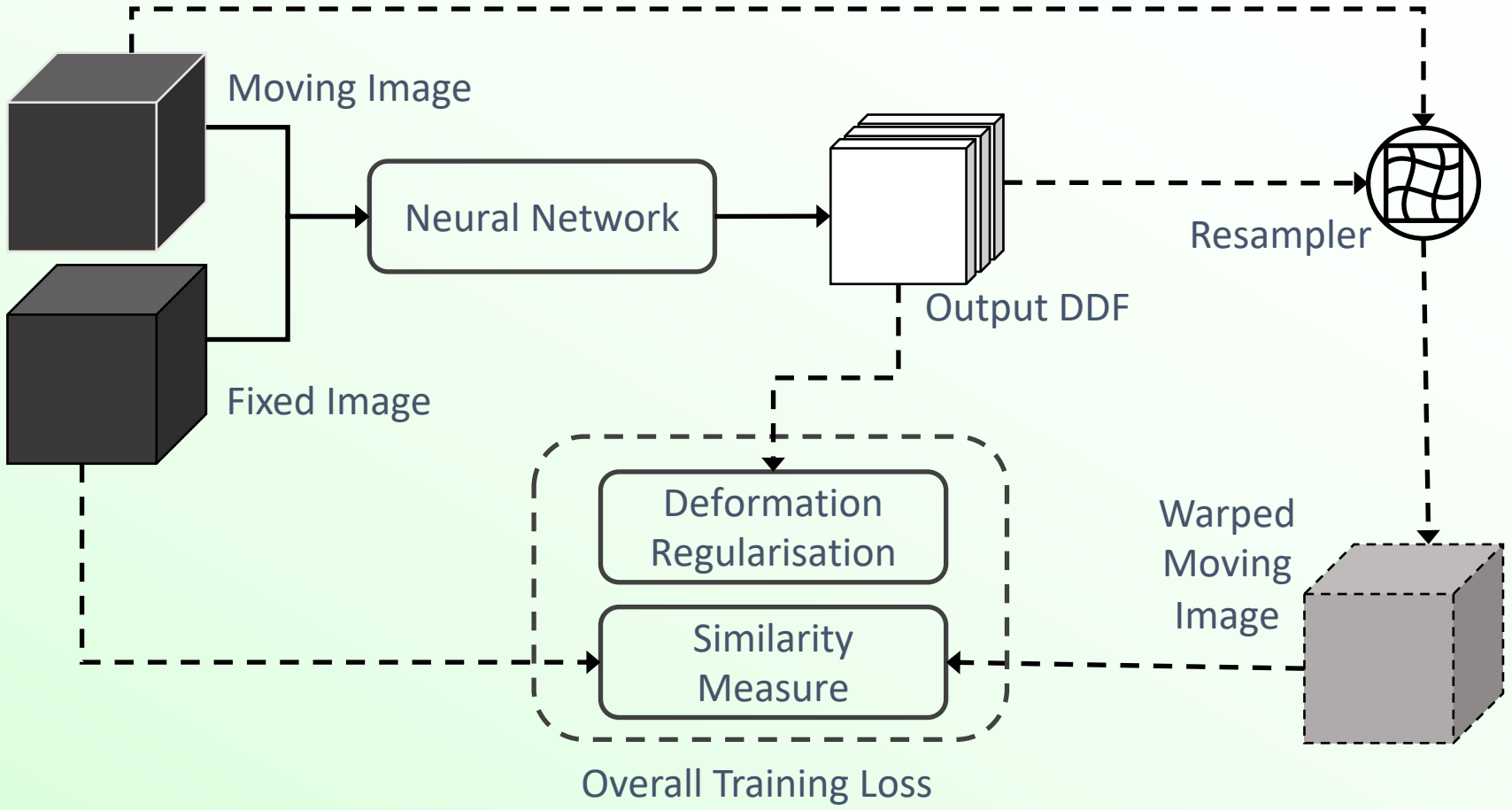
Supervised training



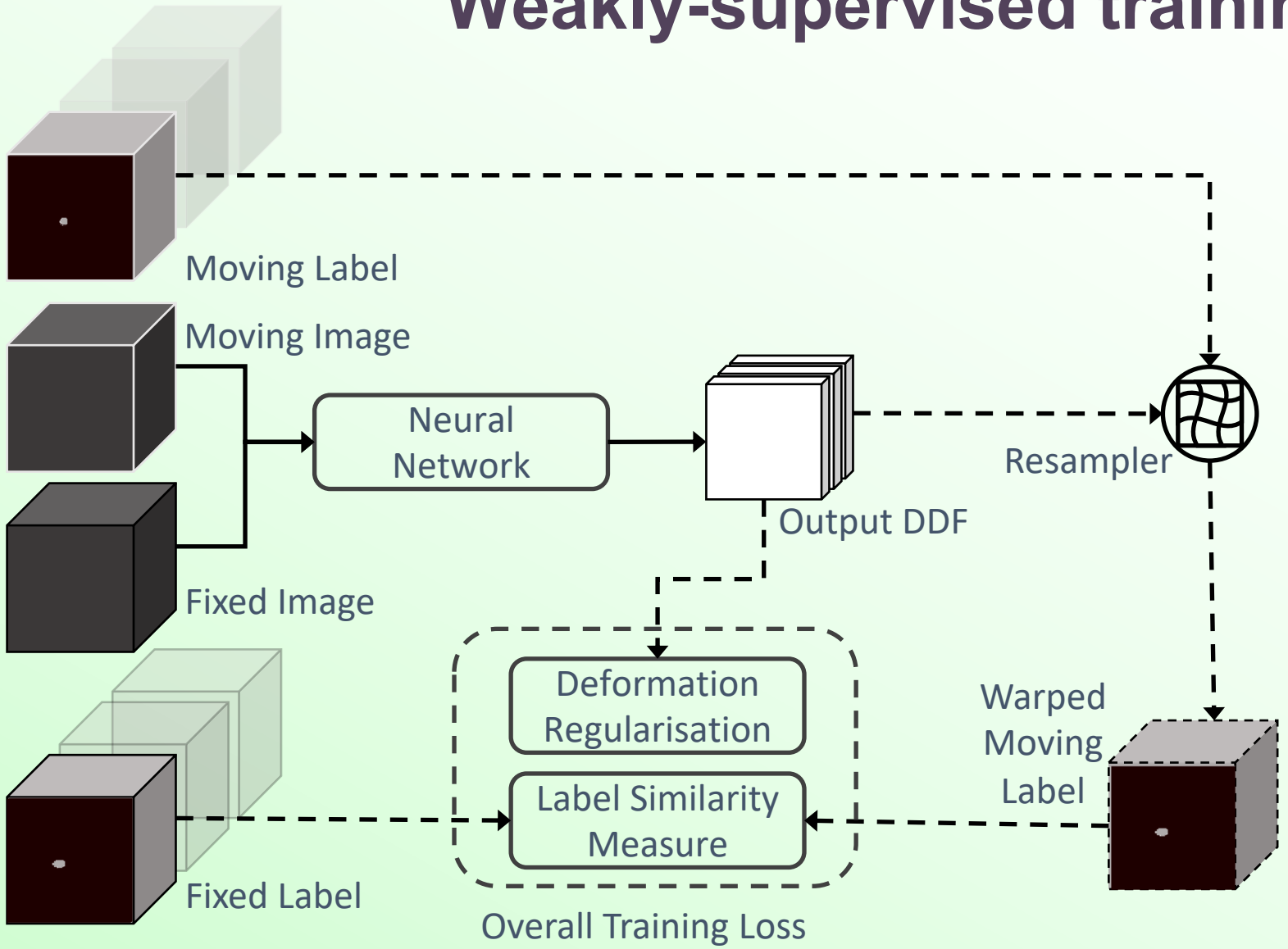
- Required ground truth transformation
  - Simulation, manual alignment, classical image registration

Self-supervised (unsupervised) training

- Training loss utilises same terms as classical image registration
- Much current research
- Well known example:
  - Voxelmorph



Weakly-supervised training



- Utilises privileged information during training:
  - Segmentations
  - Points
  - Images
  - …

Weakly-supervised training

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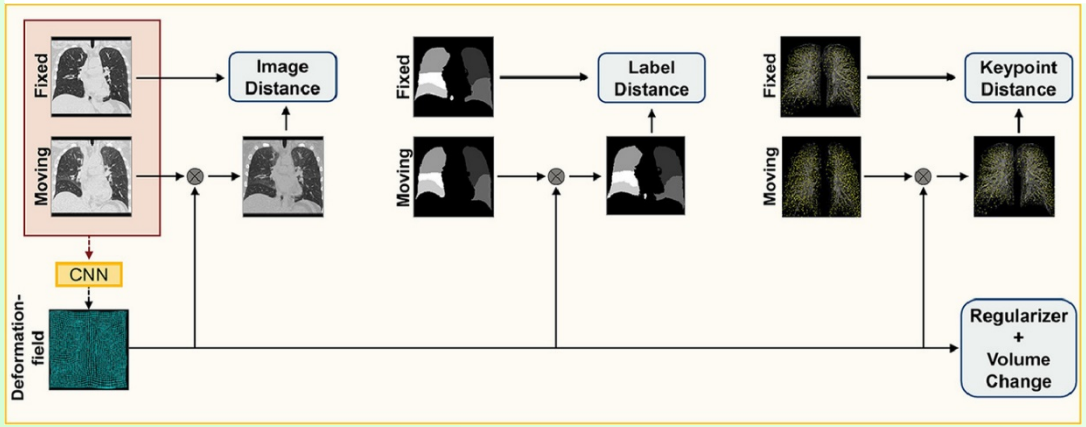
journal homepage: www.elsevier.com/locate/media

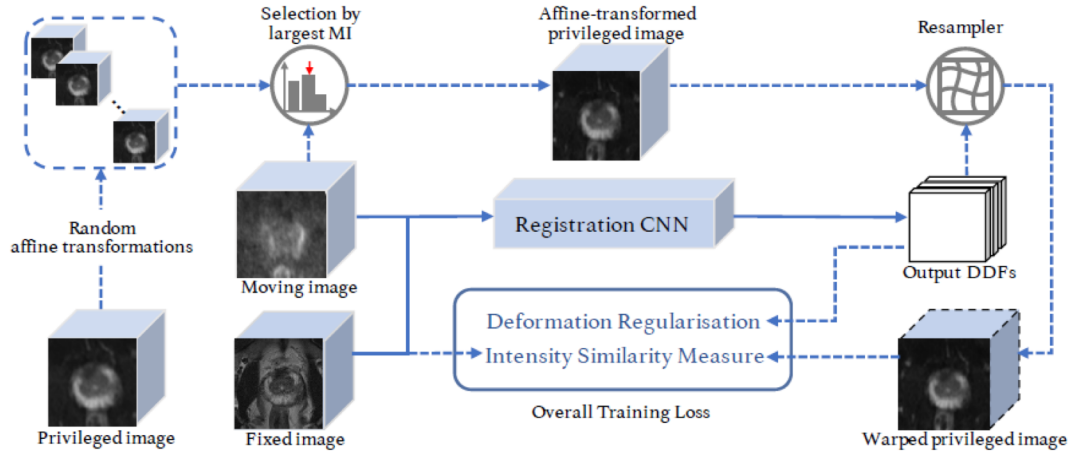
CNN-based lung CT registration with multiple anatomical constraints

Alessa Hering[a,b,*], Stephanie Häger[a], Jan Moltz[c], Nikolas Lessmann[b], Stefan Heldmann[a], Bram van Ginneken[b,c]



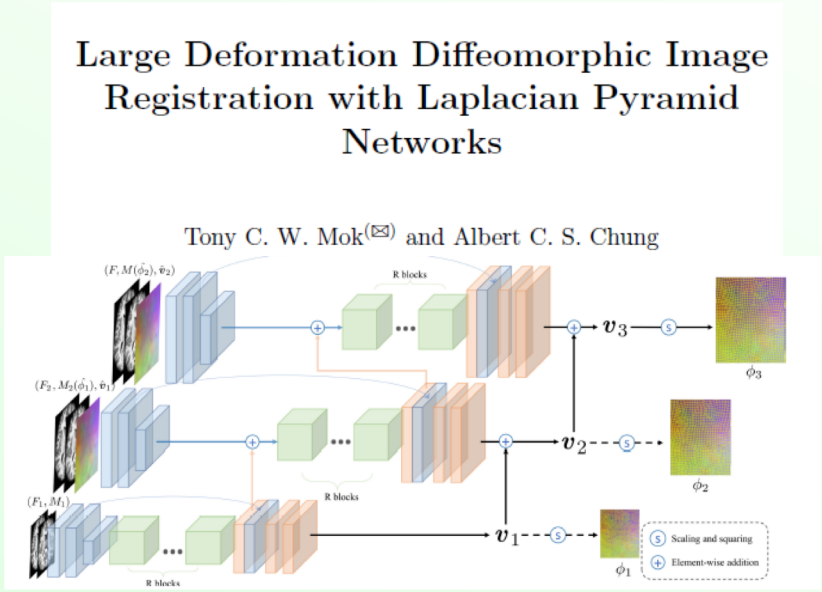
Cross-Modality Image Registration Using a Training-Time Privileged Third Modality

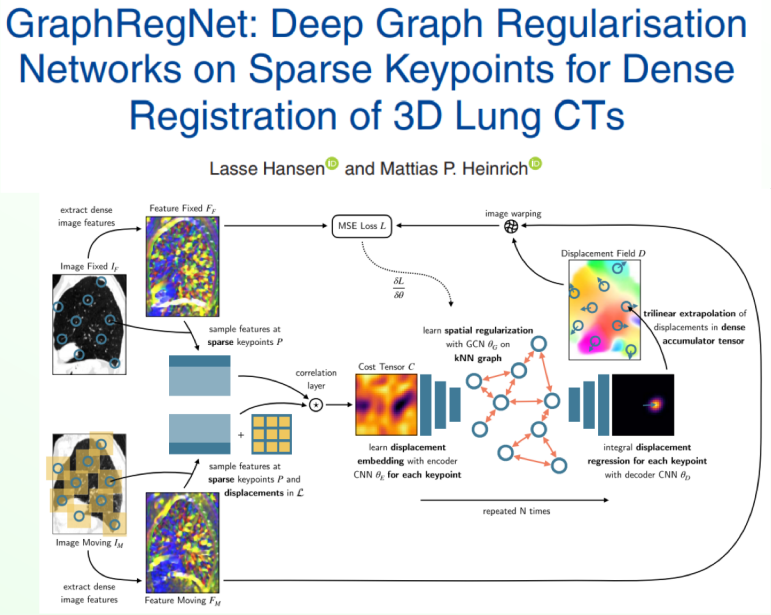
Qianye Yang, David Atkinson, Yunguan Fu, Tom Syer, Wen Yan, Shonit Punwani, Matthew J. Clarkson, Dean C. Barratt, Tom Vercauteren, and Yipeng Hu

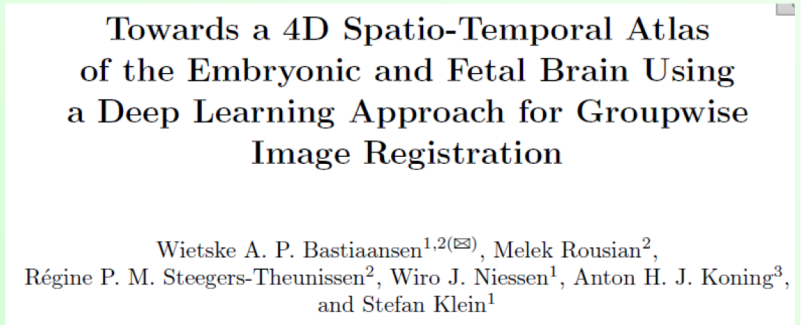


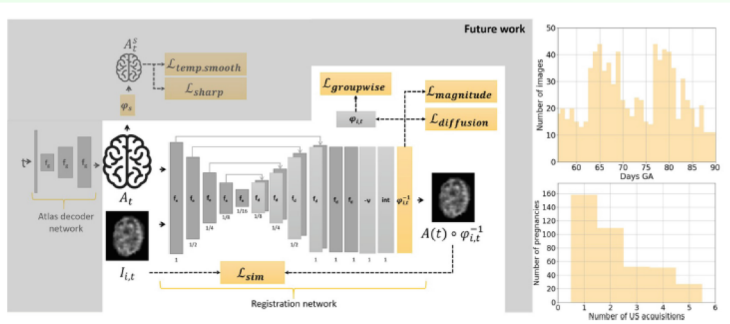
Recent(ish) developments: Inspired by classical image registration

- Diffeomorphisms
  - Velocity fields
- Multiresolution
- Feature-driven
- Graph based
- 4D







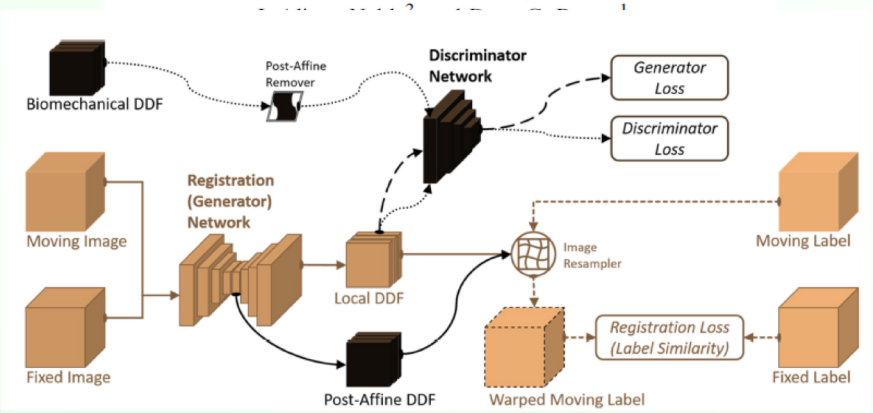


Recent(ish) developments: Inspired by advances in DL

- GANs and adversarial learning
- Diffusion networks
- Vision transformers
- Uncertainty

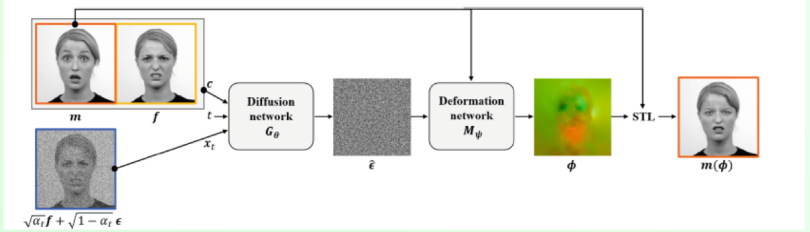
Adversarial Deformation Regularization for Training Image Registration Neural Networks

Yipeng Hu[1,2(✉)], Eli Gibson[1], Nooshin Ghavami[1], Ester Bonmati[1], Caroline M. Moore[3], Mark Emberton[3], Tom Vercauteren[1],



DiffuseMorph: Unsupervised Deformable Image Registration Using Diffusion Model

Boah Kim, Inhwa Han, and Jong Chul Ye(✉)



Recent(ish) developments: Inspired by advances in DL

- GANs and adversarial learning
- Diffusion networks
- Vision transformers
- Uncertainty

TransMorph: Transformer for unsupervised medical image registration

Junyu Chen[a,b,*], Eric C. Frey[a,b], Yufan He[c], William P. Segars[c], Ye Li[d], Yong Du[a]

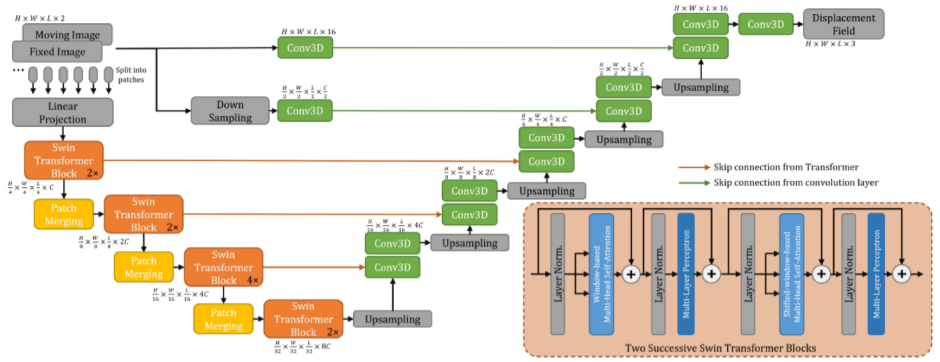
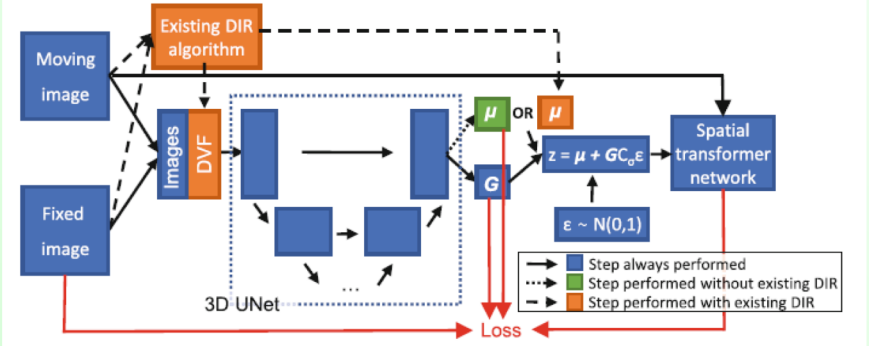


Fig. 1: The architecture of the proposed TransMorph registration network.

Deformable Image Registration Uncertainty Quantification Using Deep Learning for Dose Accumulation in Adaptive Proton Therapy

A. Smolders[1,2(✉)], T. Lomax[1,2], D. C. Weber[1], and F. Albertini[1]

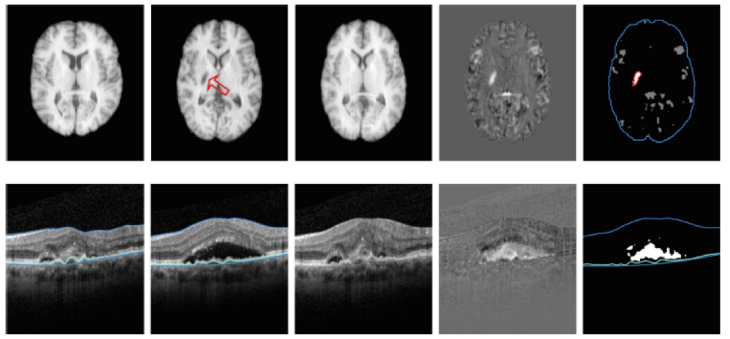


Recent(ish) developments: Others

- Changing topology
- Instance optimization
- Implicit neural representations

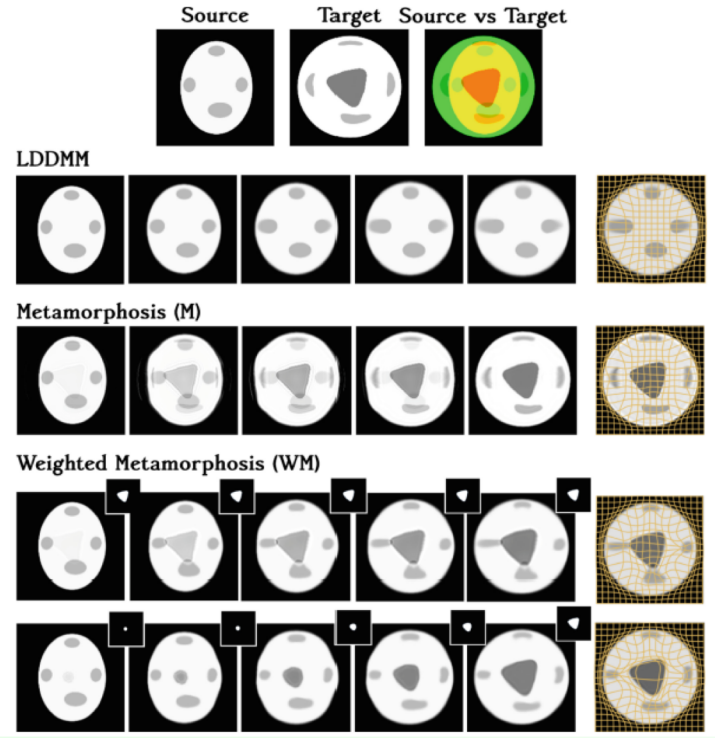
Unsupervised Non-correspondence Detection in Medical Images Using an Image Registration Convolutional Neural Network

Julia Andresen[1(✉)], Timo Kepp[1], Jan Ehrhardt[1,2], Claus von der Burchard[3], Johann Roider[3], and Heinz Handels[1,2]



Weighted Metamorphosis for Registration of Images with Different Topologies

Anton François[1,2(✉)], Matthis Maillard[2], Catherine Oppenheim[3], Johan Pallud[3], Isabelle Bloch[2,4], Pietro Gori[2(✉)], and Joan Glaunès[1(✉)]



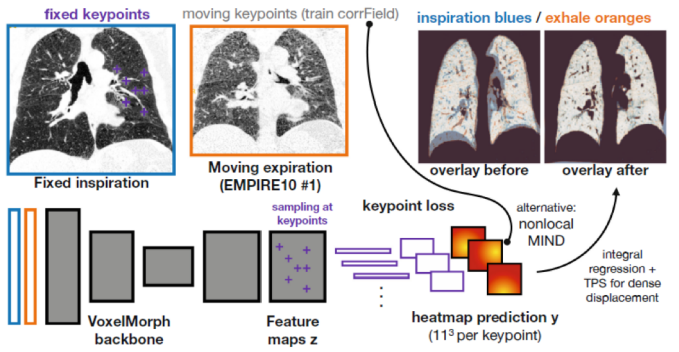
Recent(ish) developments: Others

- Changing topology
- Instance optimization
- Implicit neural representations

Voxelmorph++

Going Beyond the Cranial Vault with Keypoint Supervision and Multi-channel Instance Optimisation

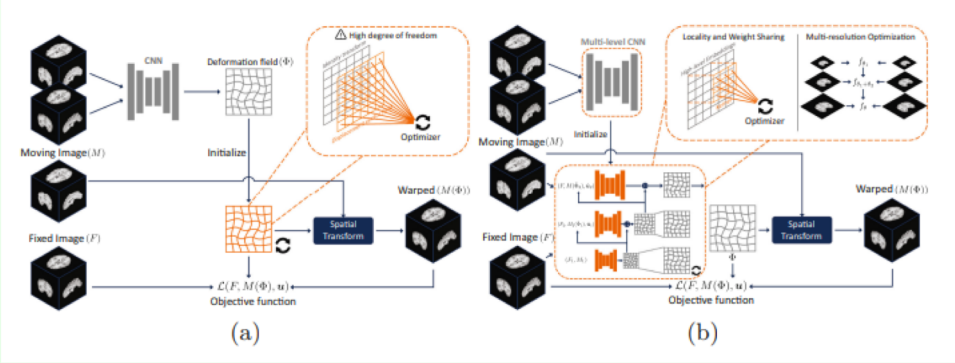
Mattias P. Heinrich and Lasse Hansen



Deformable Medical Image Registration Under Distribution Shifts with Neural Instance Optimization

Tony C. W. Mok[1,2(✉)], Zi Li[1,2], Yingda Xia[1], Jiawen Yao[1,2], Ling Zhang[1], Jingren Zhou[1,2], and Le Lu[1]

[1] DAMO Academy, Alibaba Group, Hangzhou, China
mokchi-wing.mcw@alibaba-inc.com
[2] Hupan Lab, Hangzhou 310023, China

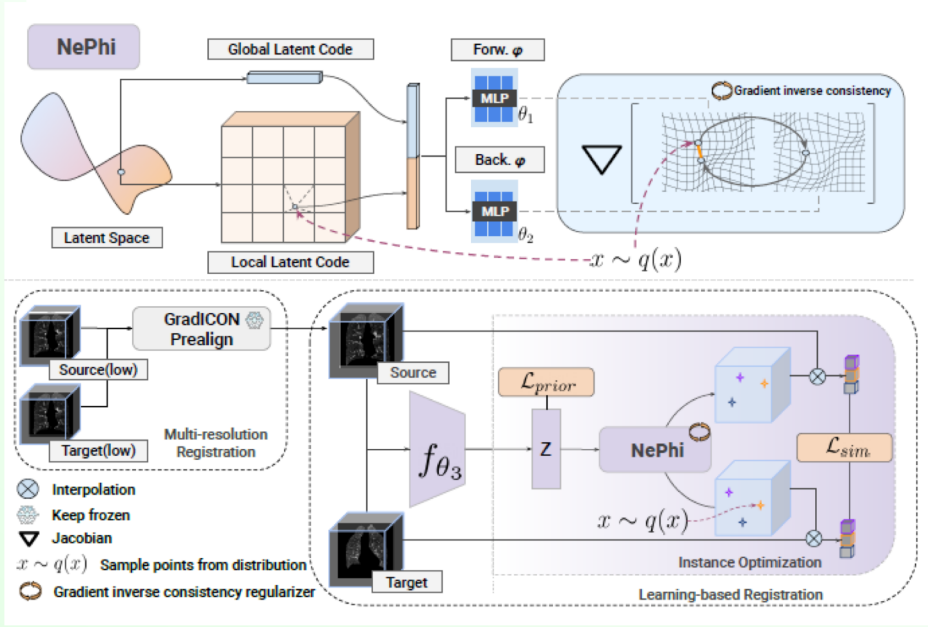


Recent(ish) developments: Others

- Changing topology
- Instance optimization
- Implicit neural representations

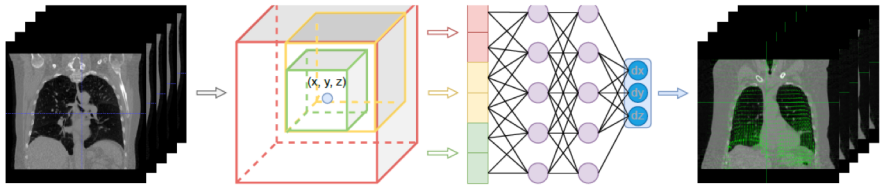
NePhi: Neural Deformation Fields for Approximately Diffeomorphic Medical Image Registration

Lin Tian[1], Hastings Greer[1], Raúl San José Estépar[2], Soumyadip Sengupta[1], and Marc Niethammer[1]



Neural Graphics Primitives-based Deformable Image Registration for On-the-fly Motion Extraction

Xia Li[1,2], Fabian Zhang[2], Muheng Li[1,3], Damien Weber[1,4,5], Antony Lomax[1], Joachim Buhmann[2], and Ye Zhang[1]

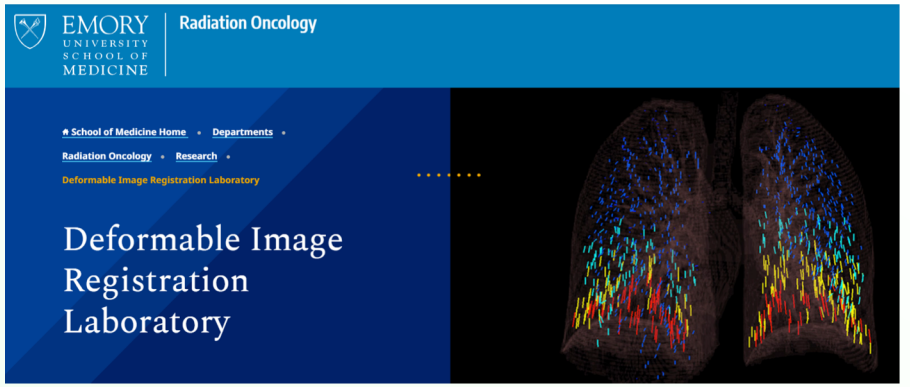


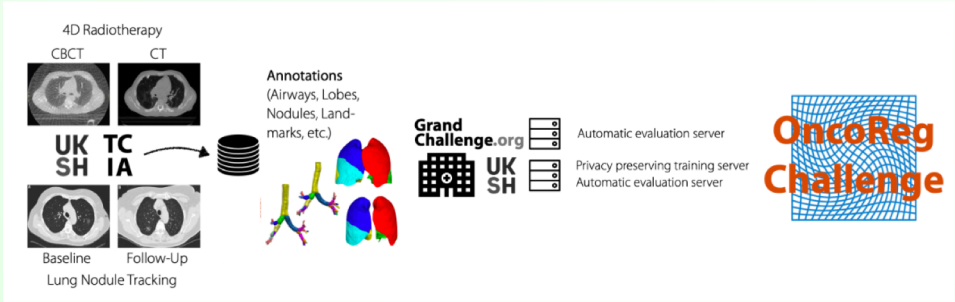
The future of medical image registration…

- Less focus on novel methods, more focus on clinical translation
  - What are the important clinical applications?
  - What do we want the registration to do?
  - How do we know if it's doing it?
- Classical or learning based?

Open datasets and challenges

- Super useful resources
- Drive innovation
- Fair comparisons between methods
- May not reflect current clinical challenges
- Sharing tools and data for evaluation





What do we really want the registration to do?

- Application specific
  - Clear for some, not for others
  - How will registration be used?
- Requires thought
- Need to be precise

And how do we know if it's doing it?

- Appropriate metrics for specific application
- Commissioning vs QA
- Applications specific cost/loss functions

Classical vs learning-based registrations

- Speed
- Computational resources
- Data requirements
- Flexibility
- Generalizability
- Use of structures for guiding registrations
- Hybrid approaches

Acknowledgments

- Present and former members of rtic
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- Collaborators and Funders:

NHS University College London Hospitals NHS Foundation Trust

The Christie NHS FOUNDATION TRUST

NHS Guy's and St Thomas' NHS Foundation Trust

NHS Cambridge University Hospitals NHS Foundation Trust

MANCHESTER 1824 The University of Manchester

ICR The Institute of Cancer Research

NPL National Physical Laboratory

RTTQA Radiotherapy Trials Quality Assurance

KING'S College LONDON

AUCKLAND BIOENGINEERING INSTITUTE THE UNIVERSITY OF AUCKLAND NEW ZEALAND Te Whare Wānanga o Tāmaki Makaurau

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UKRI Engineering and Physical Sciences Research Council

wellcome

Thanks for listening…
…any questions?