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# Deep learning for medical image registration

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#### **Outline for today:**

- First hour:
  - Quick recap of medical image registration
  - Introduction non-parametric / deformable image registration
  - Deep learning for medical image registration:
    - Deep iterative registration
    - Supervised methods
    - Unsupervised (optimization-based) methods
- Second hour:
  - Feedback on project 1
  - Question hour and example exam question



#### **Learning outcomes**

#### The student can:

- differentiate between parametric and non-parametric/deformable transformation models.
- explain what a displacement (vector) field is and calculate the corresponding number of free parameters, given a medical image pair to be registered.
- name the main advantages and disadvantages of using deep learning for medical image registration.
- categorize deep learning-based medical image registration methods into one of the three groups of methods based on how they deal with the ground truth displacement.
- For each category, give an example of a method that was proposed in recent literature.

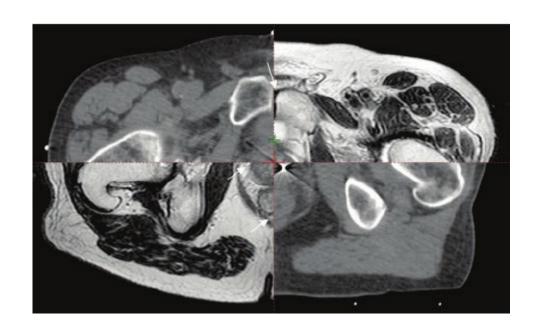
#### Recap: medical image registration

#### Why important?

- Multi-modal registration (e.g. CT on MRI)
- Inter-subject (e.g. atlas registration)
- Longitudinal (e.g. treatment evaluation)

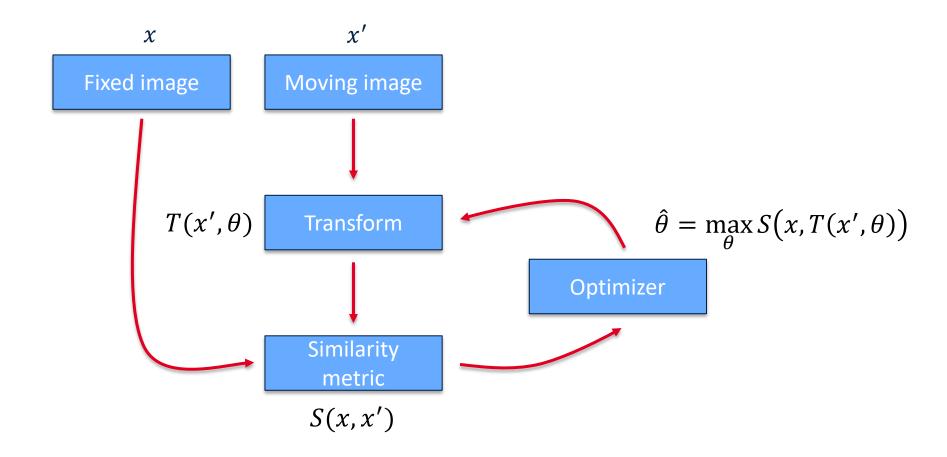
#### Remaining challenges:

- Large 3D volumes
- Accuracy vs. efficiency (speed)
- Intensity inhomogeneities and discontinuities
- Outlier rejection



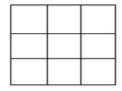


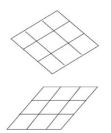
#### Finding the optimal transformation





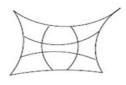
#### **Transformation models**





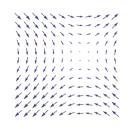
#### Rigid & Affine

- Point or feature-based (e.g. landmarks, fiducials)
- Intensity-based
- Gradient/edge-based



#### Non-linear

- Linear or higher order polynomials
- Spline-based

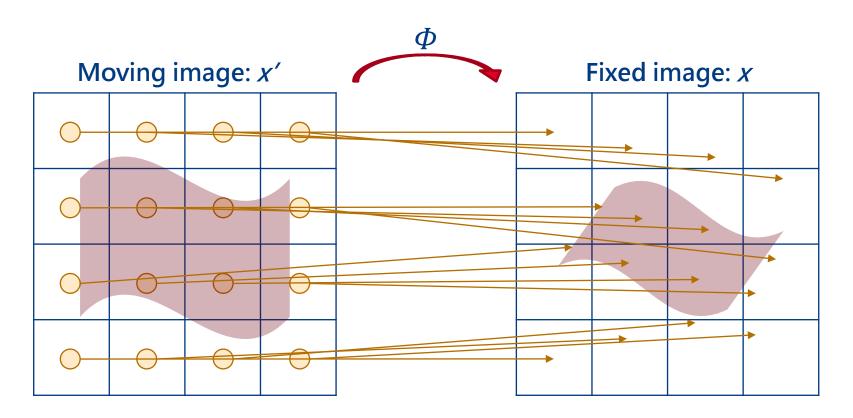


#### Non-parametric / deformable

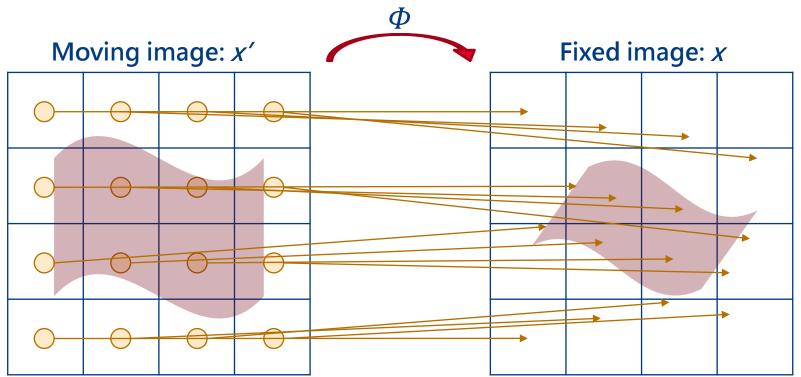
Allowing each image element to be displaced arbitrarily



**Displacement (vector) field (DVF)** = Dense set of vectors representing the displacement in a given spatial domain







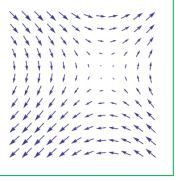
Deformation:  $\varphi = \mathrm{Id} + u$ ,  $\varphi : \Omega \to \mathbb{R}^d$ 

or point-wise:  $\varphi(x) = x + u(x)$ 

Displacement:

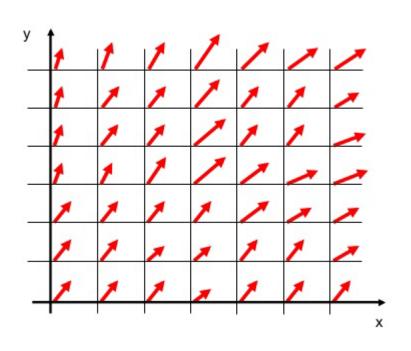
$$u: \Omega \to \mathbb{R}^d$$

e.g. 
$$u = [u_x, u_y, u_z]$$

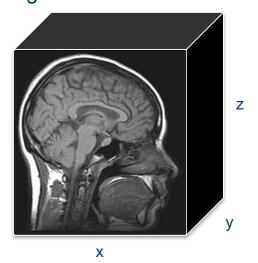




#### Deformable image registration: how many free parameters (DOF) in 3D?



Typical spatial resolution of a 3D medical image (MRI: e.g.  $1.5 \times 1.5 \times 4$  mm<sup>3</sup> voxels)



$$DOF = 3*Nx*Ny*Nz (!)$$

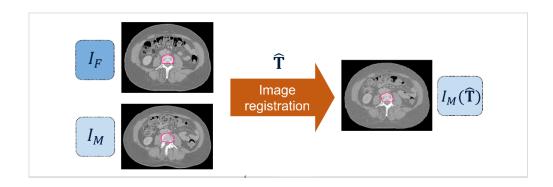
Deformable image registration is still a very active area of research, and many different deformable registration models exist:

- Free-form deformation model
- Optical flow
- Demons
- Fluid flow
- Diffeomorphisms
- ...

Note that the details of these models and their implementations are beyond the scope of this course.



#### Why focus on deep learning for medical image registration?



Real time applications!



#### Learning image registration: how does it work?

Problem: how can we obtain the ground truth displacement **T**?

#### A. Deep iterative registration

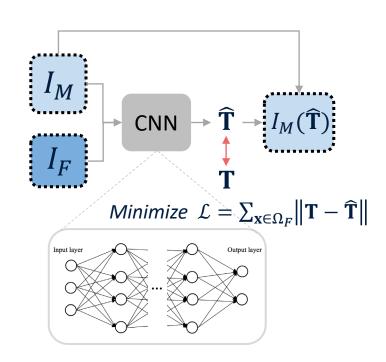
Learn a component of a classical registration method

#### B. Supervised transformation estimation

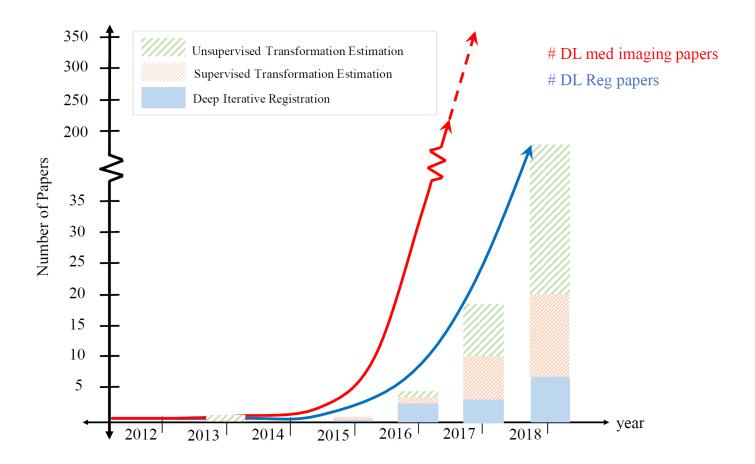
- Obtain T using classical registration method
- or make synthetic ground truth

### C. Unsupervised transformation estimation

• Use similarity metric to judge  $I_M(\widehat{\mathbf{T}})$ 



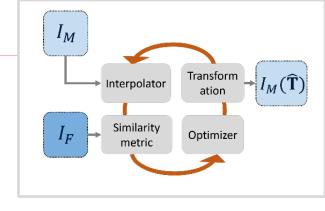
#### Publications on deep learning for medical image registration



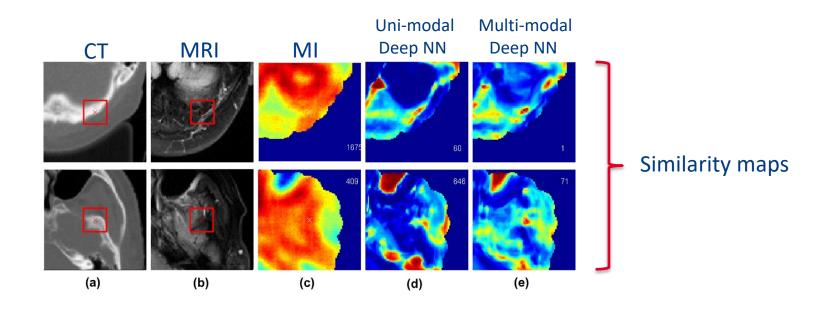


#### A. Deep iterative registration

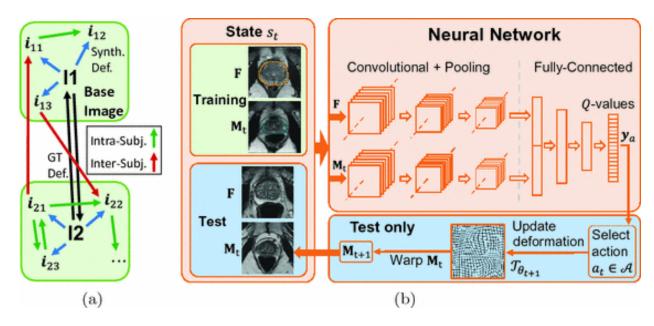
Use a classical registration method and learn one component



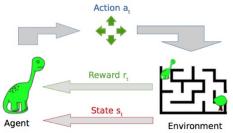
Example 1: Learning multimodal feature extraction (Haskins et al., 2019)



#### Example 2: Reinforcement learning for image registration

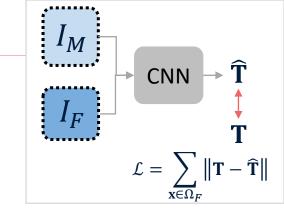


(a) Training Data Generation: **Synthetic deformations** (blue arrows) and intersubject GT deformations (black) are used for intra- (green) and inter-subject (red) image pairs for training. (b) Dual-stream network used for Q-value prediction including complete single-stage Markov Decision Process for testing (blue background).

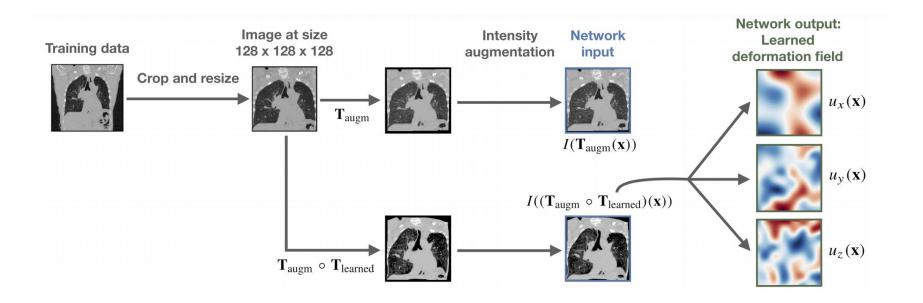


#### **B.** Supervised transformation estimation

Requires many known transformations for training, use ground truth labels to calculate the loss

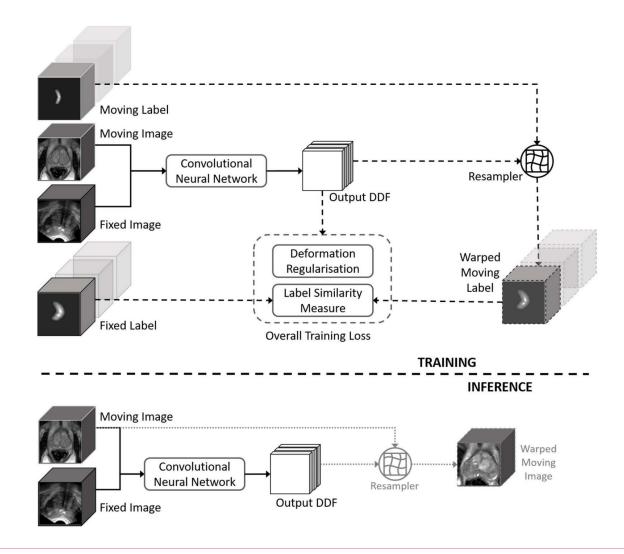


Example 1: "On-the-fly" simulation of displacement fields: T<sub>augm</sub> (Eppenhof & Pluim, 2018)





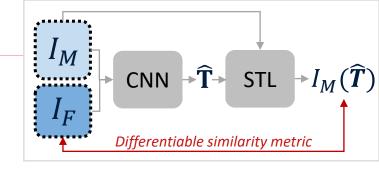
#### Example 2: Weakly-supervised CNN for MR-US registration



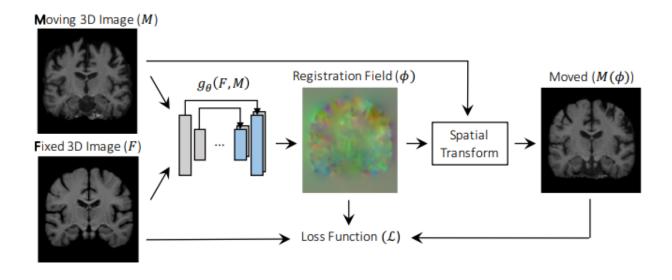


# C. Unsupervised transformation estimation

No ground truth needed, requires a differentiable similarity metric and a spatial transformer layer (STL).



#### Example 1: the VoxelMorph framework (Balakrishnan et al., 2018)

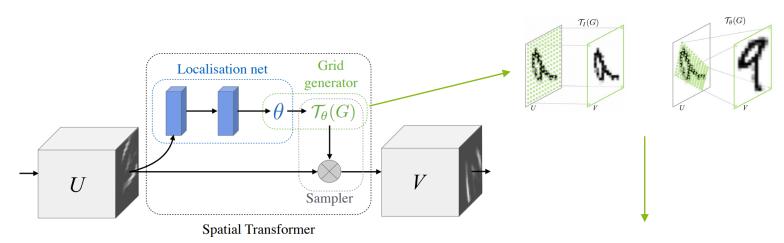




#### Spatial transformer networks (Jaderberg et al., NIPS 2015)

**Spatial transformer** = a learnable module that explicitly allows the spatial manipulation of data within the network

- Differentiable
- Can be inserted into existing convolutional neural networks
- Actively transforms feature maps (conditional on the feature map itself)



#### Example $T_{\theta}(G)$ for an affine transformation:

$$\begin{pmatrix} x_i^s \\ y_i^s \end{pmatrix} = \mathcal{T}_{\theta}(G_i) = \mathtt{A}_{\theta} \begin{pmatrix} x_i^t \\ y_i^t \\ 1 \end{pmatrix} = \begin{bmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \end{bmatrix} \begin{pmatrix} x_i^t \\ y_i^t \\ 1 \end{pmatrix}$$

#### **Summary**

- Parametric vs. non-parametric/deformable image registration
  - Displacement vector fields
- Different ways to use deep learning for image registration
  - Deep iterative registration
  - Supervised learning
  - Unsupervised learning
- Disadvantages of deep learning for image registration (performance, # of training data, ground truth, ...)



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## Feedback Project 1

#### General feedback Project 1

- Results: make sure to organize the results well, logical order, caption for each figure!
- Discussion: do the discussed topics directly follow from the results?
- Use references! NB: scientific writing
- Reproducibility: e.g. create a notebook that allows others to easily repeat the experiment or run the code

Grades and group-specific feedback have been communicated with all groups via Canvas, if have questions about this, ask your TA (or me).

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# Preparing for the exam

#### How can I prepare for the exam?

- (Re)study all exercises (NB: open questions)
  - Answers on Canvas (soon)
- Questions in the lecture slides
- Group exercises lecture 2 by Seb ("Deep learning frameworks & applications")
- Practice exam

Example exam question: registration case study

#### 7. Case 1: Neuronavigation

The neurosurgery department recently acquired a new neuronavigation system with a probe (Figure 2) that is depicted on the computer screen showing the MRI scan of the patient. The system relies on a registration between N extrinsic fiducials depicted on the MRI scan and the physical fiducials.

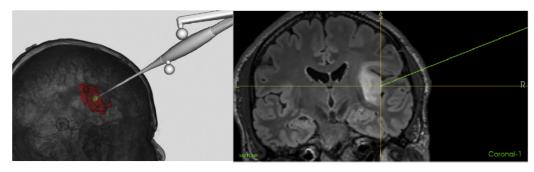


Figure 2: Three-dimensional rendering of the preoperative MRI scan and the probe (left), and a coronal slice of the MRI scan (right).

A nice feature of the navigation system is that it allows the neurosurgeon to check the accuracy of the registration by touching some points of the patient's anatomy with the probe, after which the system calculates an estimate of the registration error. Halfway through the first surgery, the neurosurgeon wants to perform a "sanity check" of the registration and touches all N fiducials with the probe. The surgeon then decides to omit the fiducial with the largest error and repeats the registration based on the remaining N-1 fiducials.



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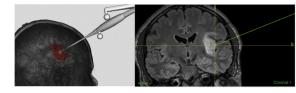


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- 1. What type of registration problem is this?
  - (a) Uni-modal
  - (b) Multi-modal
  - (c) Longitudinal
  - (d) Atlas-based
  - (e) None of the above
- 2. Which transformation model is required?
  - (a) Deformable
  - (b) Affine
  - (c) Rigid
  - (d) Non-linear
- 3. Which image similarity metric is used for the registration?
  - (a) Sum of square differences
  - (b) (Normalized) cross-correlation
  - (c) Mutual information
  - (d) None of the above
- 4. How can you find the optimal transformation?
  - (a) Gradient ascent
  - (b) Gradient descent
  - (c) Use reinforcement learning
  - (d) Solve the orthogonal Procrustes problem
  - (e) Solve  $X'X^T(XX^T)^{-1}$
- 5. Which metric should be used to evaluate the registration performance?
  - (a) Sensitivity
  - (b) Dice similarity coefficient (DSC)
  - (c) Target registration error (TRE)
  - (d) Accuracy
  - (e) Hausdorff distance
  - (f) Specificity

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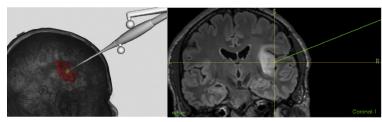


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(b) (4 points) Open question (max. 100 words): Explain what will happen with the fiducial registration error (FRE) and the target registration error (TRE) after dropping this fiducial. What do you think of this sanity check and the effect on the accuracy of the navigation system?