Image Registration

Preview of the Biomedical Image Processing Course

Courtesy of Dr. Alessandro Daducci

Outline

Introduction

- What is image registration?
- Motivaton and main applications

Problem formulation

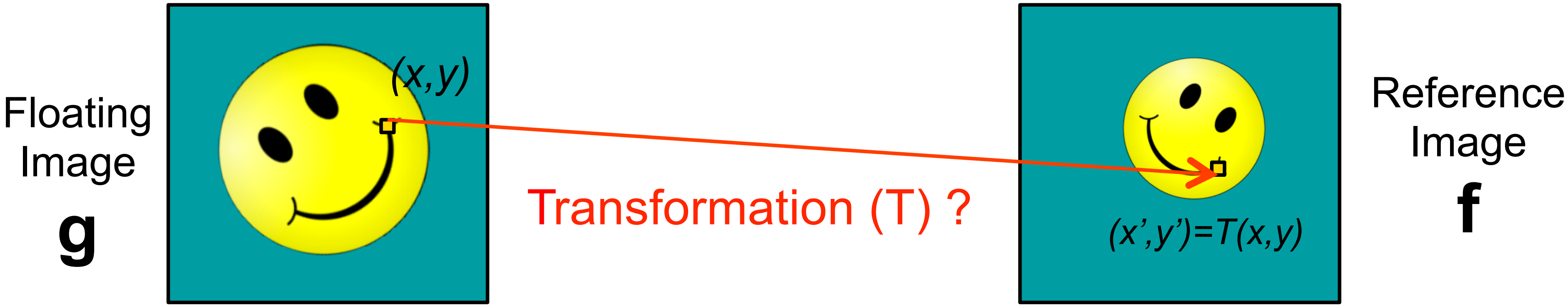
- Mathematical definiton
- General framework

Main components

- *Features* : which information to use in the registration
- *Similarity metrics* : measure how similar two images are
- *Transforms* : deformation model to transform one image into another
- *Optimizers* : algorithm to estimate the transformation
- *Interpolators* : how to compute common coordinates from different images

Image registration

Registration is the **process of finding the transformation** (T) that puts different images (**f** and **g**) into spatial correspondence



Example

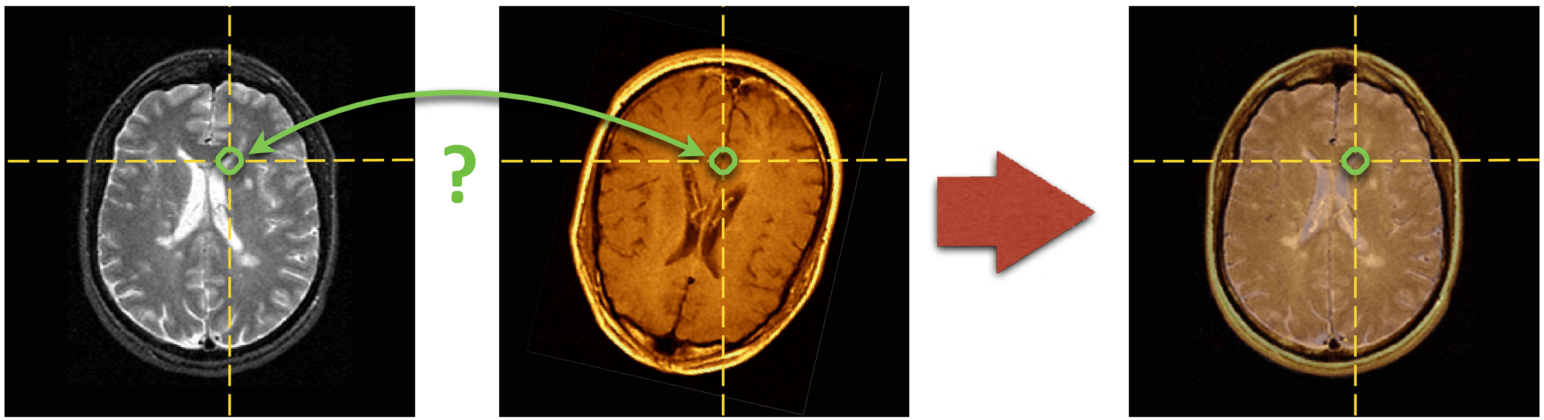
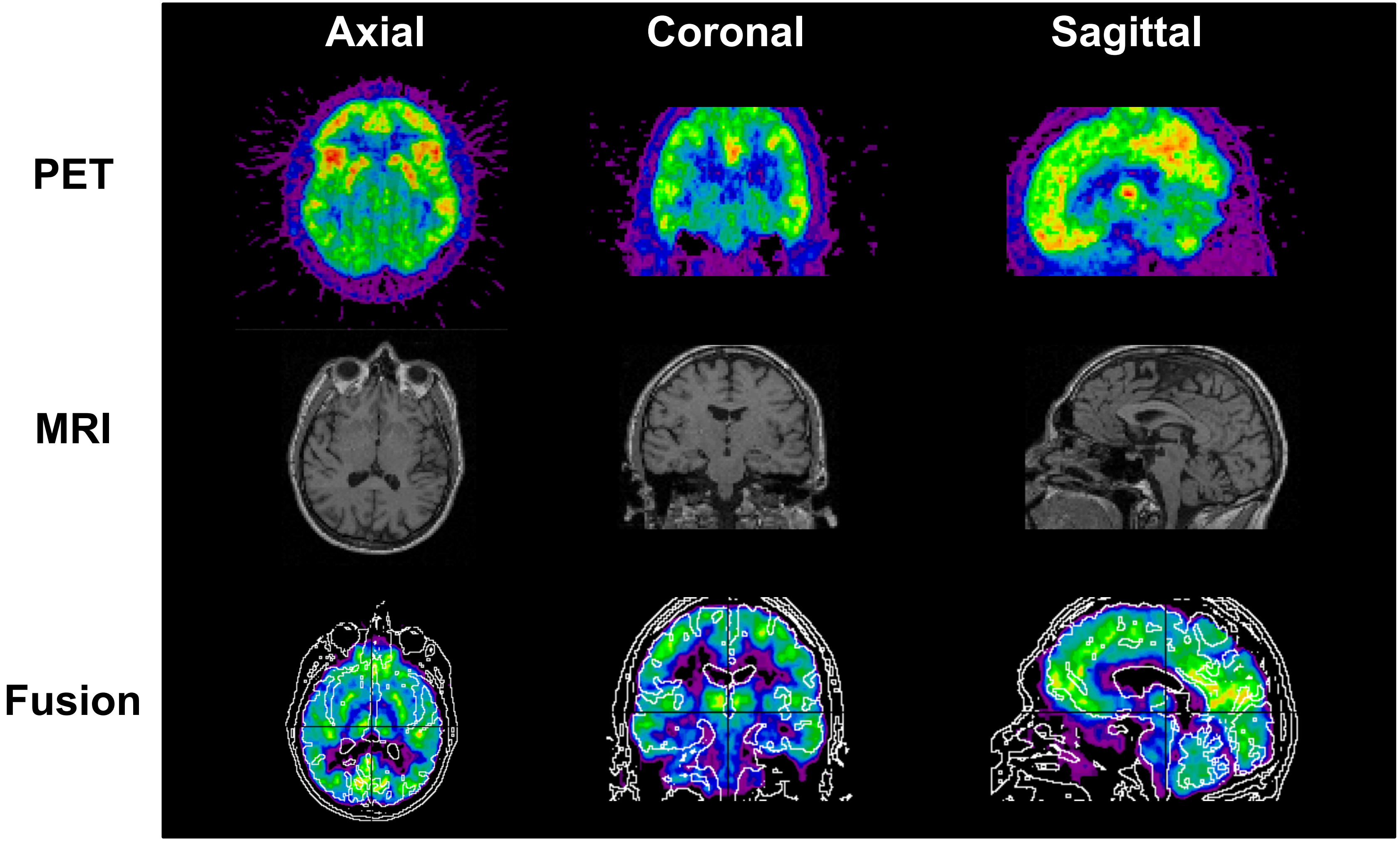


image **f** image **g** **g** registered to **f**

Why do we need to register medical images?

Improve diagnosis

- Combining information from multiple imaging modalities

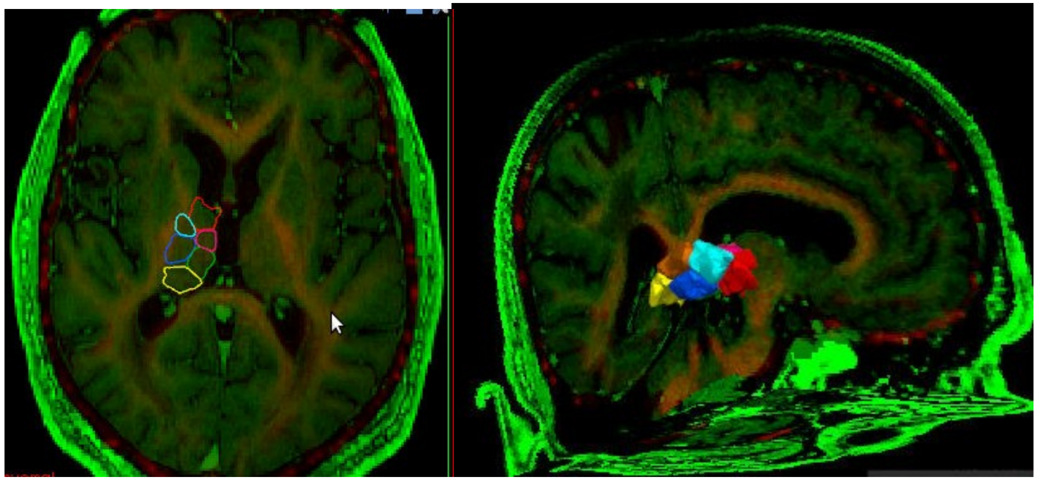


Why do we need to register medical images? (2/7)

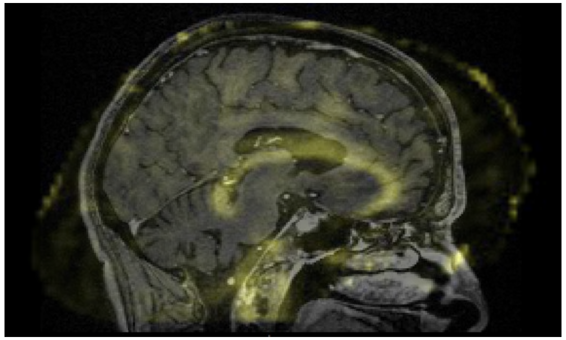
Image guided surgery or radiotherapy

- Image guided surgery or radiotherapy

After registration



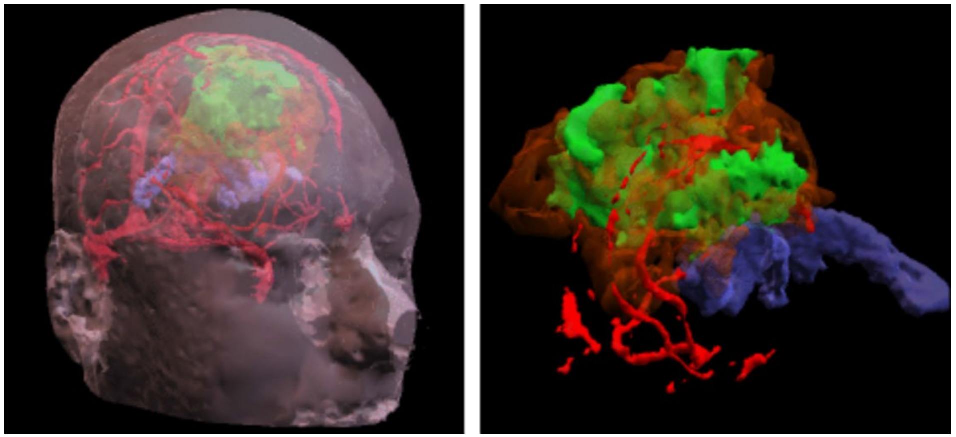
Before registration



VIM targeting for therapy of movement disorders

- **T1w** : thalamus segmentation/delineation
- **DWI** : clustering of thalamus nuclei

(PhD thesis of E. Najdenovska @ EPFL)



Why do we need to register medical images?

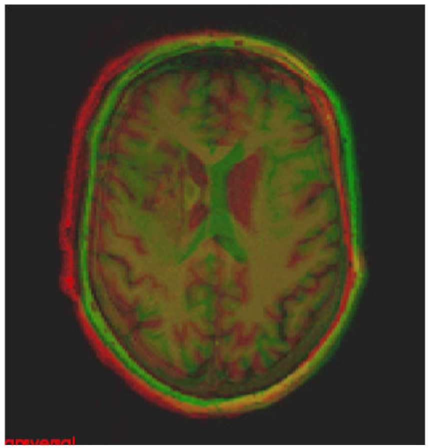
Study **disease progression**

- Monitoring changes in size, shape, position or image intensity over time

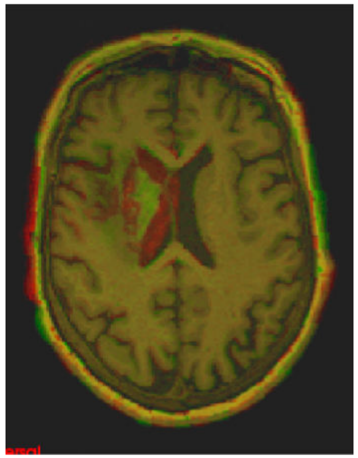
2000 **2001** **2002**

Time 1

Time 2



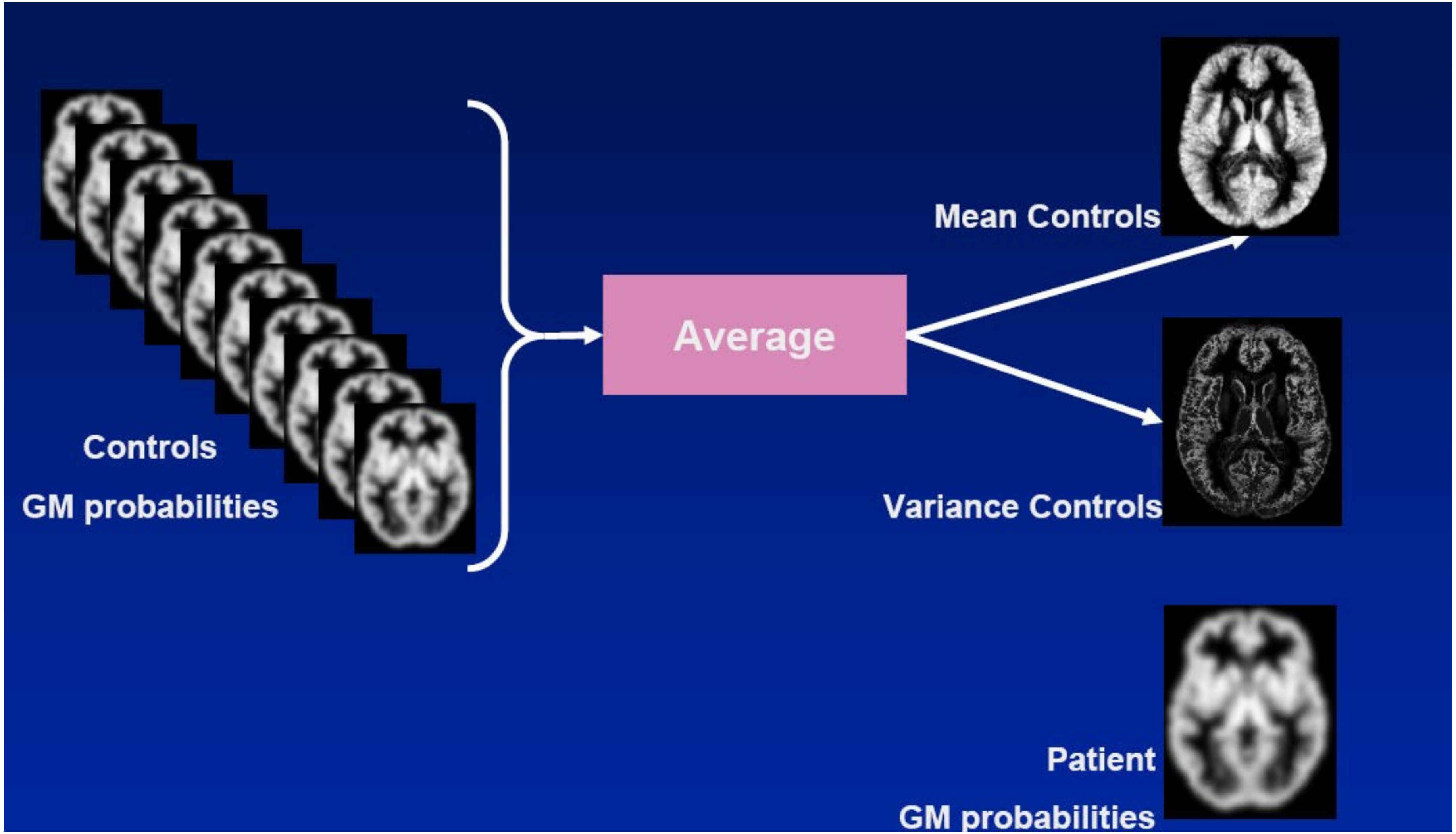
Before registra. on



AFer registra. on

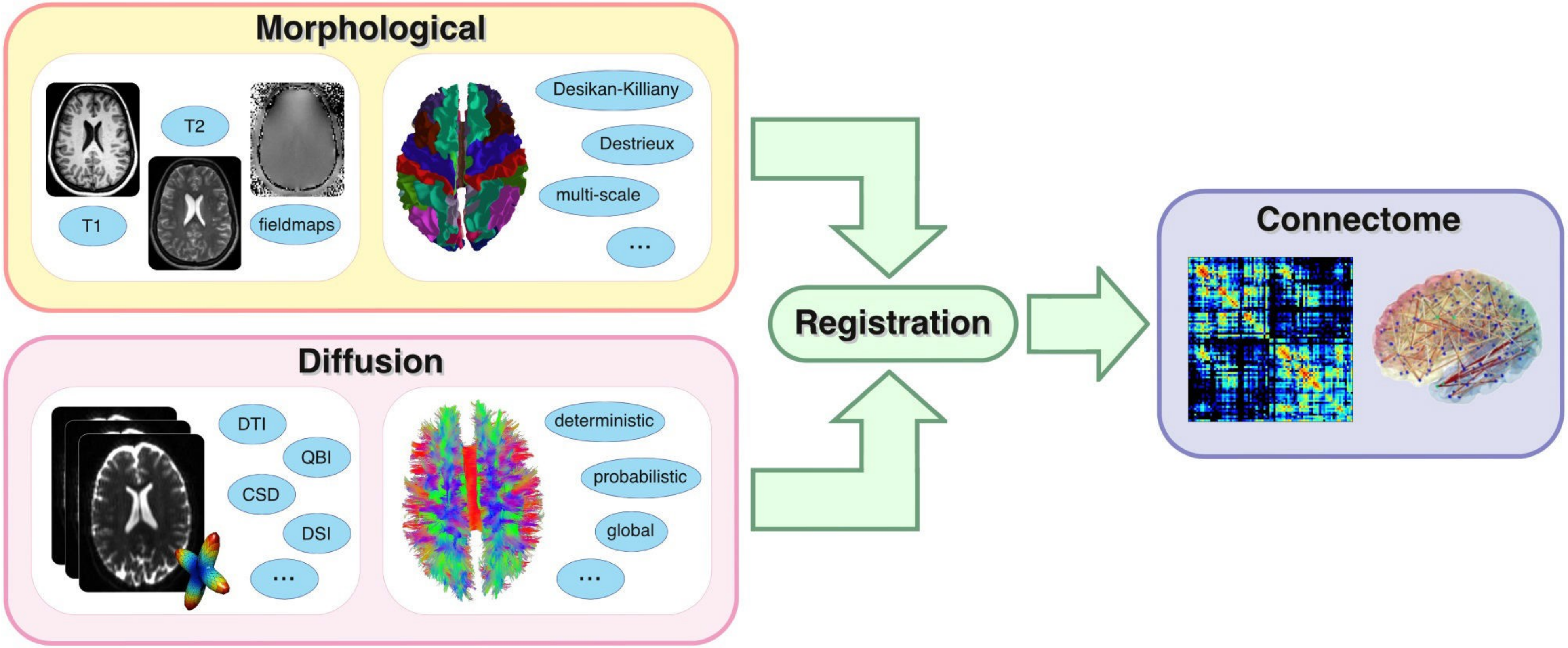
Why do we need to register medical images?

- **Patient comparison** (group studies) or **atlas construction**
  - Relating one individual's anatomy to a standardized atlas or group of subjects



Why do we need to register medical images?

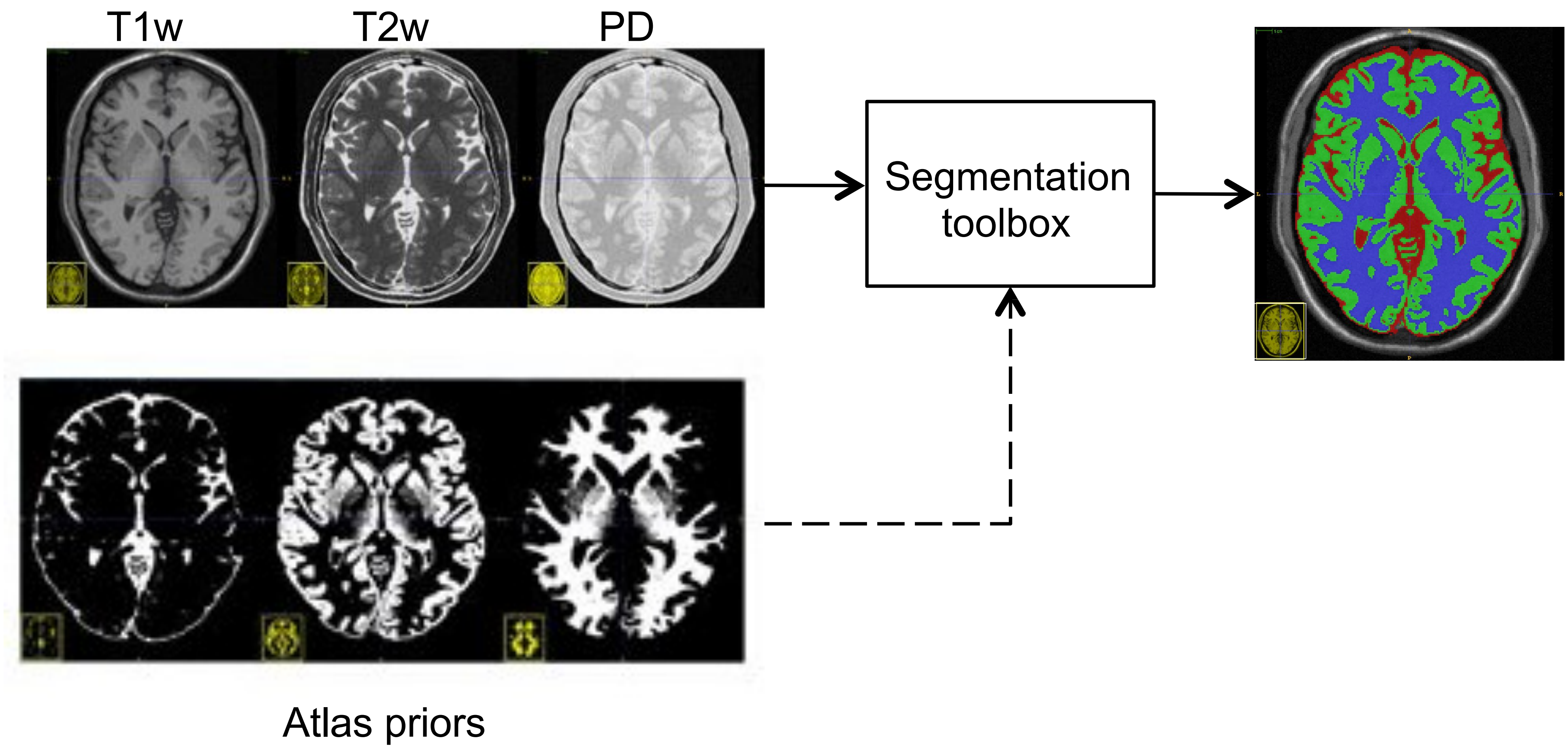
- Estimating **brain connectivity** from diffusion MRI
  - Estimate *fiber bundles* from diffusion MRI, i.e. DWI
    - Define *cortical segmentation* from structural MRI, e.g. T1w



http://hardi.epfl.ch

Why do we need to register medical images?

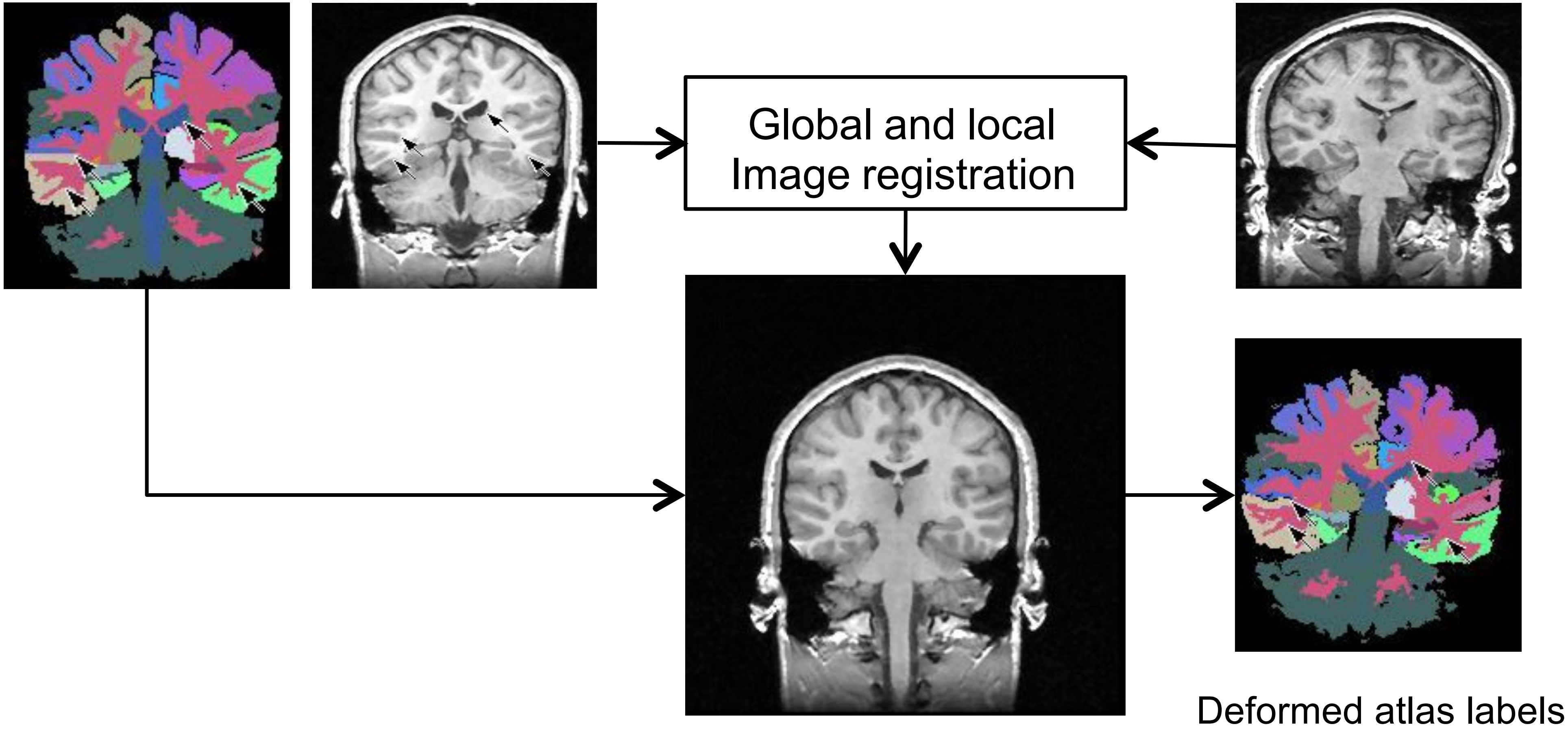
- Multispectral **segmentation**
  - Use more than one modality to improve the segmentation of brain anatomy



(PhD thesis of O. Esteban @ Madrid+EPFL)

Why do we need to register medical images?

- Atlas-based **segmentation**
  - Use an accurate atlas to define one subject's anatomy

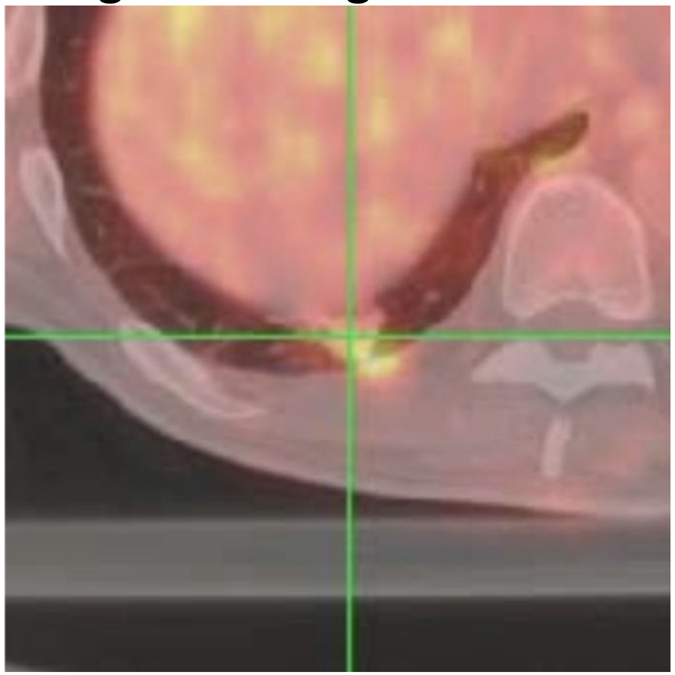


(PhD thesis of S. Gorthi @ EPFL)

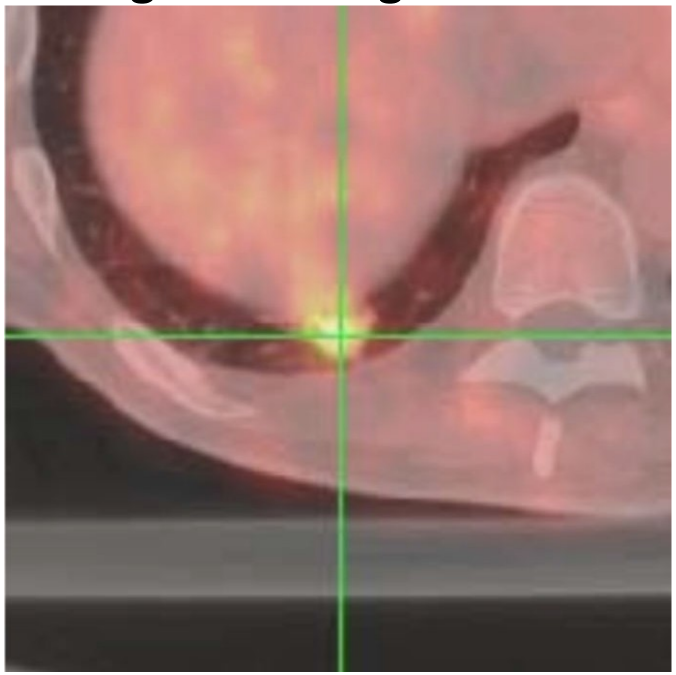
Registration is very important

- In **medical imaging**, registration is particularly important
  - **Example**: *PET-MRI* registration to study tumor location

Registra.on algorithm 1



Registra.on algorithm 2

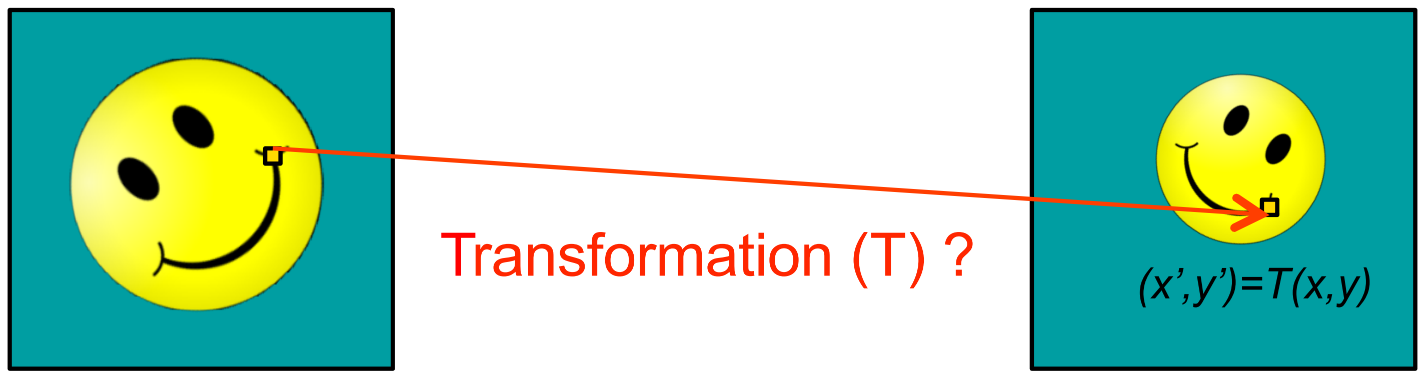


  - Is the tumor in the lung only?

Mathema. cal formula. on

- Registration is an **alignment problem**
  - "*...find the spatial transformation* that maps points from one image B to the corresponding points in another image A..."

(x,y)



Mathematical formulation

Registra5on is an **alignment problem**

- “*…find the spa5al transforma5on* that maps points from one image B to the corresponding points in another image A…”

Usually solved as **energy minimization problem** (or maximization)

optimal transformation

$$\mathcal{T}^* = \underset{\mathcal{T} \in \mathbb{T}}{\operatorname{argmin}} \, d(A, B^{\mathcal{T}})$$

images

space of all possible transformations

similarity/dissimilarity between the images

Nota5on

- $A : \mathbf{x}_A \in \Omega_A \mapsto A(\mathbf{x_A})$ Intensity of image A at location $\mathbf{x}$
- $\mathbf{T} : \mathbf{x}_B \mapsto \mathbf{x}_A \iff \mathbf{T}(\mathbf{x}_B) = \mathbf{x}_A$ Transforms a position $\mathbf{x}$ from one image to another
- $\mathcal{T}$ Transforms an image (both coordinates $\mathbf{x}$ and
- $B^{\mathcal{T}}$ intensities) Image B transformed
- $\Omega^{T}_{A,B} = \{\mathbf{x}_A \in \Omega_A | \mathbf{T}^{-1}(\mathbf{x}_A) \in \Omega_B\}$ Overlap domain after transformation $\mathbf{T}$

Mathematical formulation

General framework

Target Image → Feature → Cost function/Metric → Optimizer

Source Image → Feature → Interpolator ← Transform

The main actors

- **Feature**

-Which information to use for driving the registration

- **Similarity metric**

-Measures of how similar the features are in the two images

- **Interpolator**

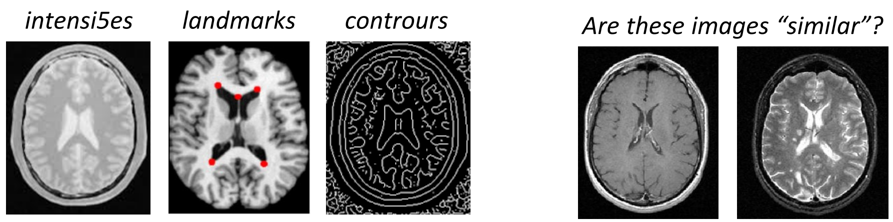
-How to compute similarity metrics from different grids

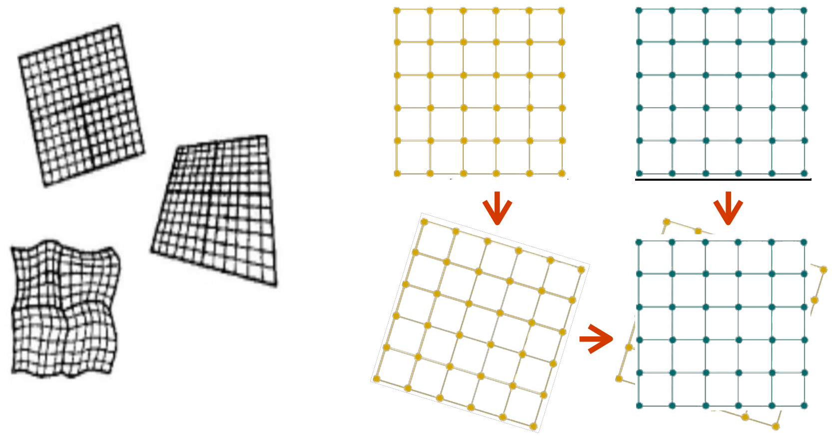
- **Transform**

-The deformation model to transform one image into another

- **Optimizer**

-The optimization algorithm to estimate the transformation

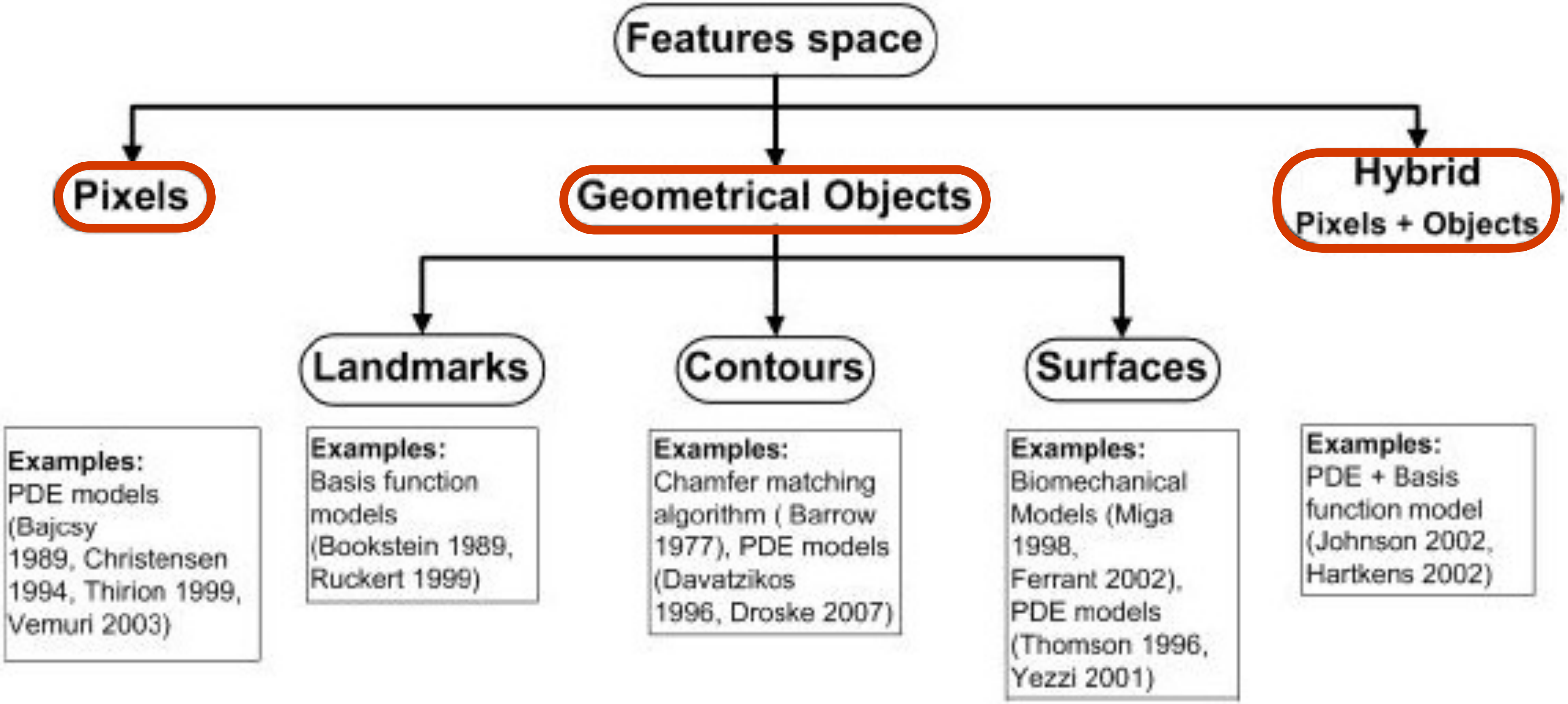




I - Features of interest

Two main approaches

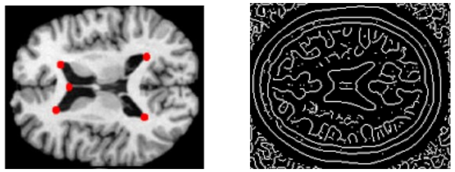
- **Feature based**: use corresponding points or features in the images to align them
  - **Intensity based**: operate directly on the image intensi5es



(PhD thesis of V. Duay @ EPFL)

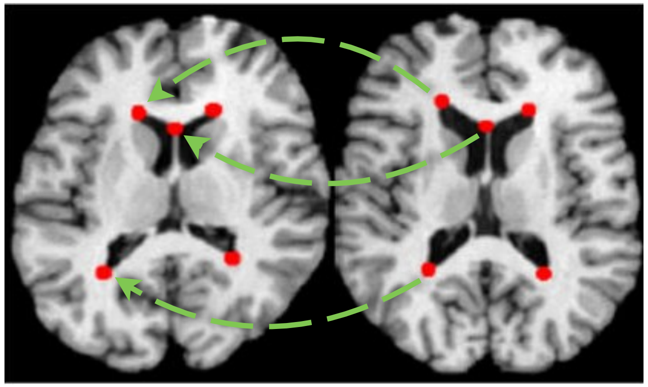
I - Features of interest

Feature based approach



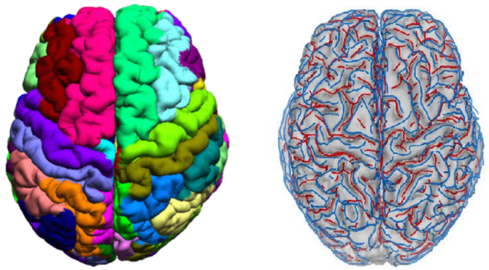
- Extract corresponding features from both images
- Compute transformation $\mathbf{T}$ by minimizing some "*measure of distance*" between them

Example: landmarks



- Identify "*fiducial markers*" on the images
  - -Internal anatomical structures, e.g. anterior commissure
  - -Pins/markers fixed to the patient, e.g. skin markers
- *Compute the centroid* of each point cloud
  - -Difference between centroids = *translation* that must be applied
- *Rotate* one point-set until the *distance between corresponding points* is minimized
  - -Iterative Closest Point (ICP) algorithm

Can be extended to other features

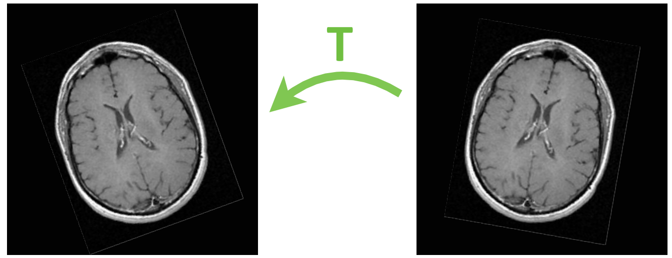


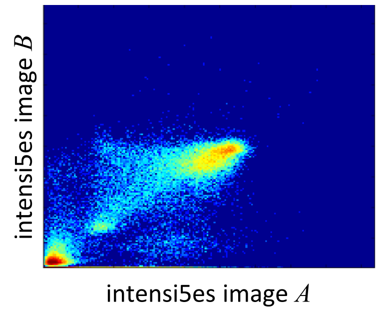
- e.g. *surfaces* ("*Head and Hat*") or *contours* ("Crest Lines")
- **Critical** : define a good *similarity metric* for that feature

I - Features of interest

Intensity based approach

- Use the intensities in the two images alone
  - No need to delineate corresponding structures
  - Like having “features = pixels”
  - Transformation $\mathbf{T}$ computed by *comparing intensity patterns* in both images via “**pixel similarity metrics**”
- These are based on the **joint histogram**



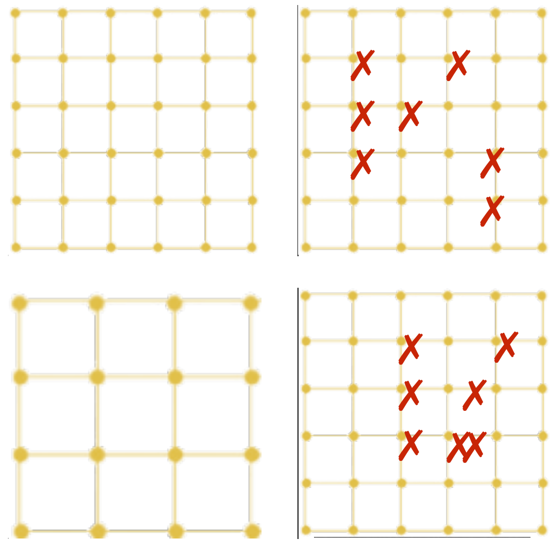


NB: we will focus on this approach

(it’s the most used in medical imaging)

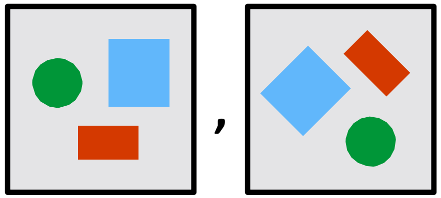
Image **sampling strategy**

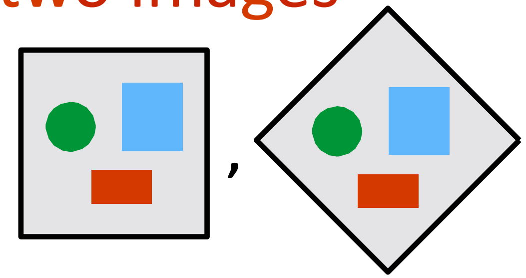
- **Full sampling**
  - Similarity metrics computed on *all voxels of the image*
- **Subset sampling**
  - In general, it is not necessary to evaluate all voxels
  - Examples : **subsampled regular grid**, **random loca.ons** …



II - Similarity measures

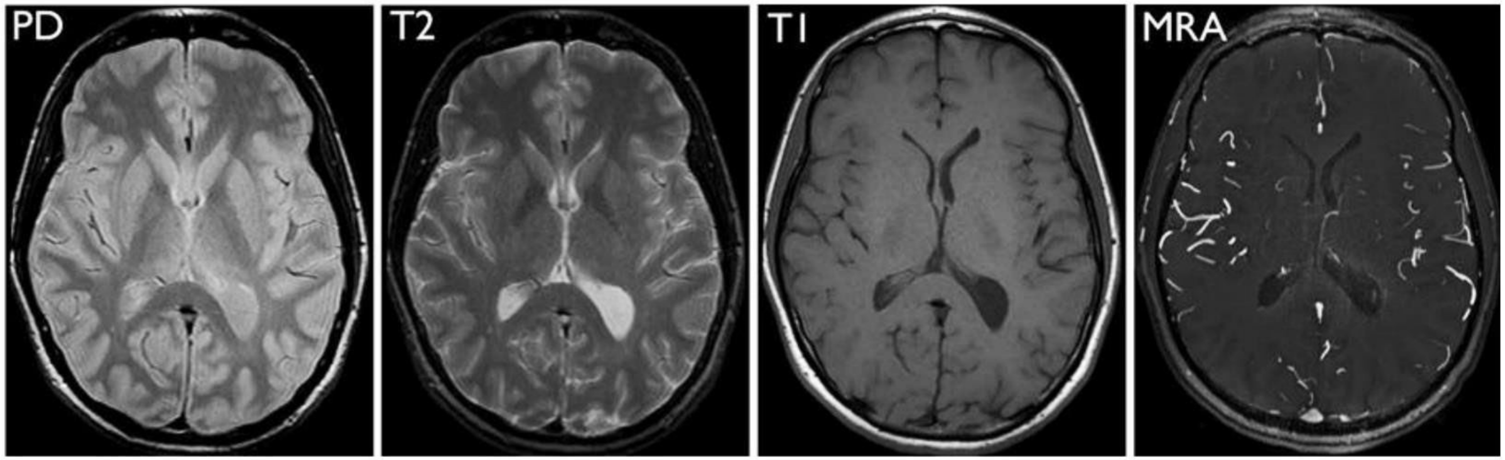
Quantify **degree of similarity** between two images

similarity() = 

similarity() = 

Example

- Same subject/session, but images from different modalities look different

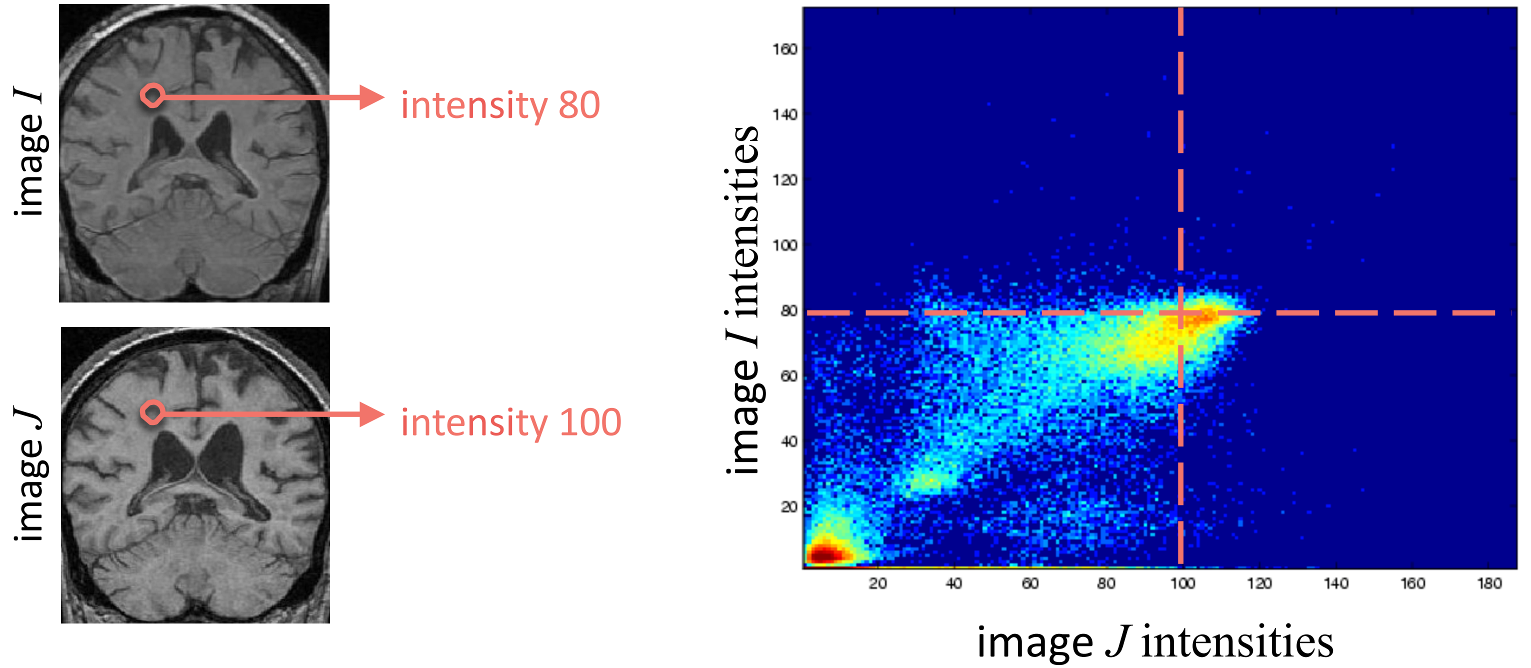


- How to construct a metric to realize they are all the “same object”? would be
- $\sum_{\mathbf{x}\in\Omega_A} |A(\mathbf{x}) - B^{\mathcal{T}}(\mathbf{x})|$ very high in any case. Any other idea?

II - Similarity measures

Joint histogram

$$H_{I,J}(i,j) = \mathrm{Card}\,\{(x,y) | I(x,y) = i \text{ and } J(x,y) = j\}$$



Notes

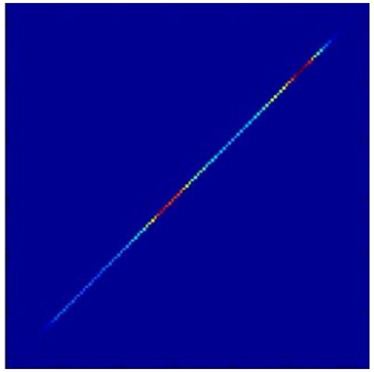
- I and J must have the *same dimensions, e.g* $M \times N$ (**NB**: in this context $J = B^{\mathcal{T}}$)
- If I and J have *intensities* in [0…255]
  - *size*($H_{I,J}$) = 256×256 and *sum*($H_{I,J}$) = $M{\cdot}N$

II - Similarity measures

Examples

image I

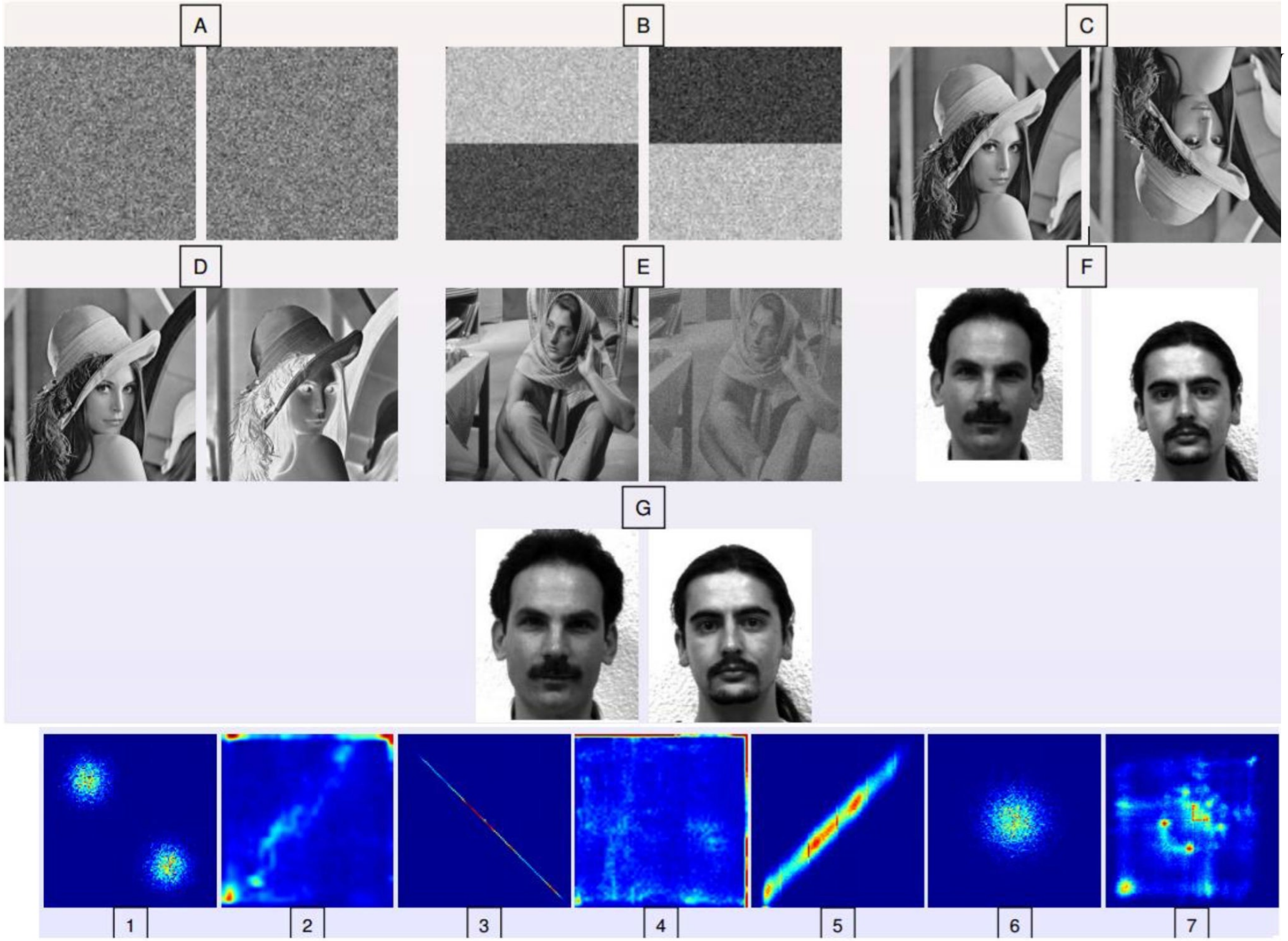
image J=I



$H_{I,J}$

II - Similarity measures

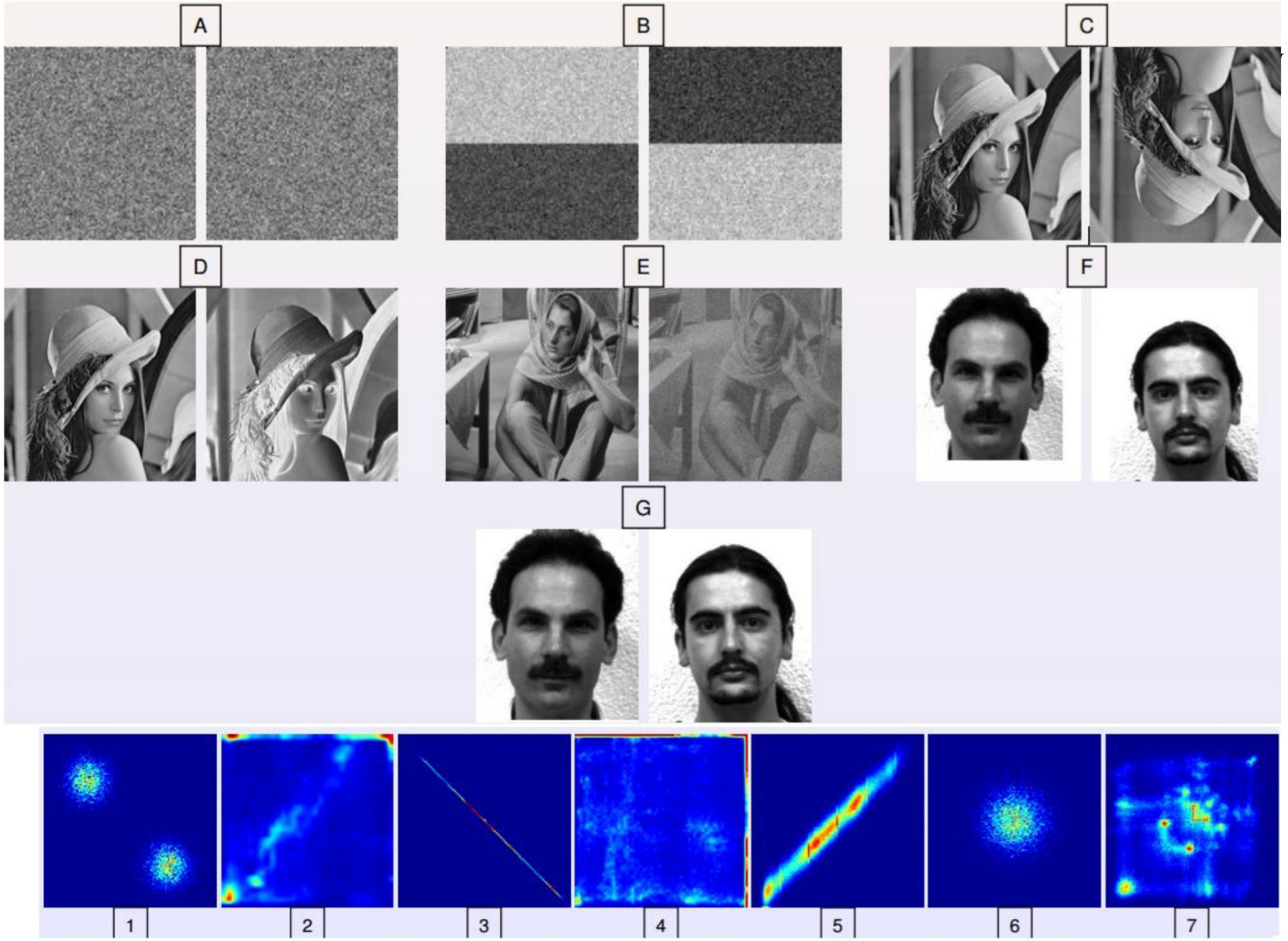
- Examples



II - Similarity measures

- Examples

A→6, B→1, C→7, D→3, E→5, F→4 , G→2



II - Similarity measures

Minimizing intensity differences

- **Sum of squared differences** (SSD)

$$\mathrm{SSD} = \sum_{\mathbf{x}_A \in \Omega^{\mathcal{T}}_{A,B}} \left| A(\mathbf{x}_A) - B^{\mathcal{T}}(\mathbf{x}_A) \right|^2$$

- SSD *very sensitive* to few voxels with very different intensities between images
  - e.g. contrast agent is injected between two acquisi5ons
  - **Sum of absolute differences** (SAD) reduces the effect of these outliers

$$\mathrm{SAD} = \sum_{\mathbf{x}_A \in \Omega^{\mathcal{T}}_{A,B}} \left| A(\mathbf{x}_A) - B^{\mathcal{T}}(\mathbf{x}_A) \right|$$

Notes

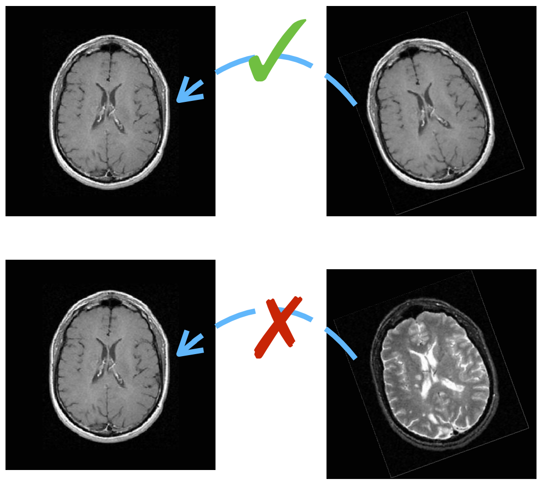
- Computed from $H_{I,J}$: $\quad \mathrm{SSD} = \sum_{i,j} H(i,j) \cdot (i-j)^2$

- SSD/SAD can be used only when “images are the same”

-Same *modality*, same *contrast*, same *scaling, same visible details…*

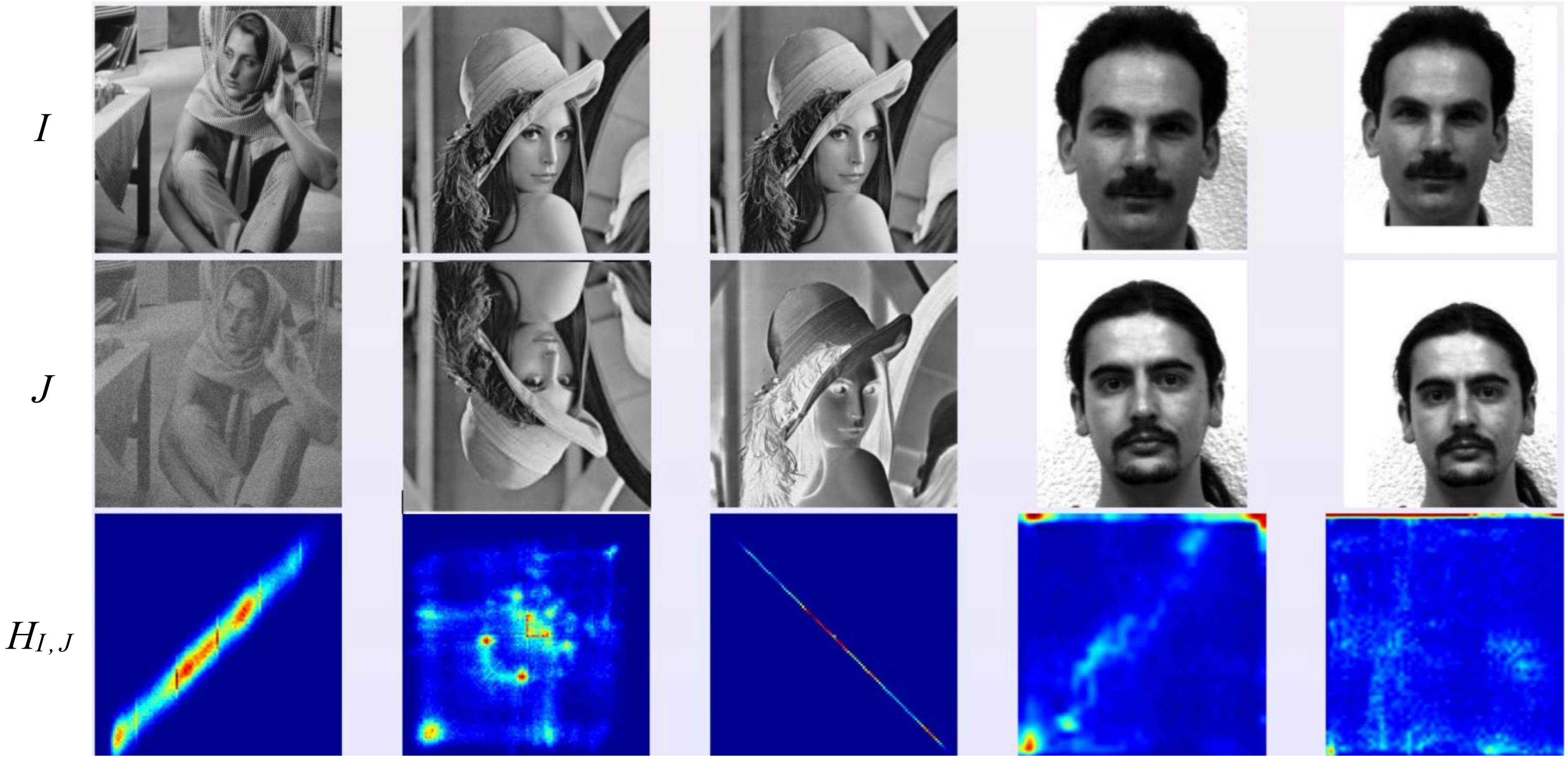
-…but, in practice, this is never the case

-*Implicit assumption*: after registration the images differ only by Gaussian noise



II - Similarity measures

SSD examples



SSD	652	10^9	10^{10}	5600	13400

II - Similarity measures

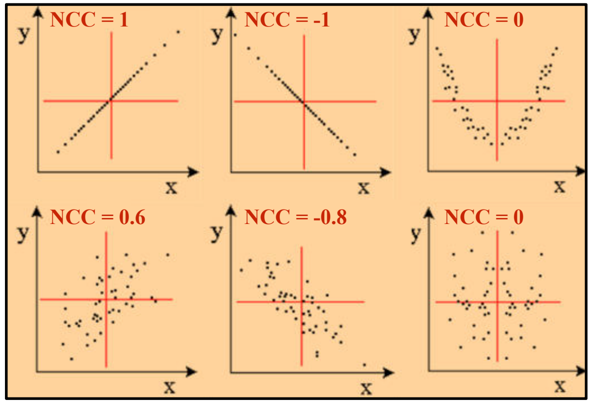
Correla. o n approach

- Use a *slightly less strict assump5on*
  - We don't try to have $B^{\mathcal{T}} = A$ at registra5on
  - We require only a rela5onship of the form $B^{\mathcal{T}} = \alpha A + \beta$ (linear)
  - **Cross-Correla.on** (CC)

$$\mathrm{CC} = \sum_{\mathbf{x}_A \in \Omega^{\mathcal{T}}_{A,B}} A(\mathbf{x}_A) \cdot B^{\mathcal{T}}(\mathbf{x}_A)$$

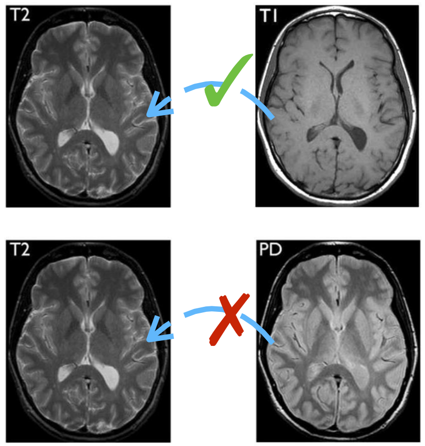
- **Normalized Cross-Correla.on** (NCC)

$$\mathrm{NCC} = \frac{\sum_{\mathbf{x}_A \in \Omega^{\mathcal{T}}_{A,B}} (A(\mathbf{x}_A) - \bar{A}) \cdot (B^{\mathcal{T}}(\mathbf{x}_A) - \bar{B})}{\sqrt{\sum_{\mathbf{x}_A \in \Omega^{\mathcal{T}}_{A,B}} (A(\mathbf{x}_A) - \bar{A})^2} \cdot \sqrt{\sum_{\mathbf{x}_A \in \Omega^{\mathcal{T}}_{A,B}} (B^{\mathcal{T}}(\mathbf{x}_A) - \bar{B})^2}}$$



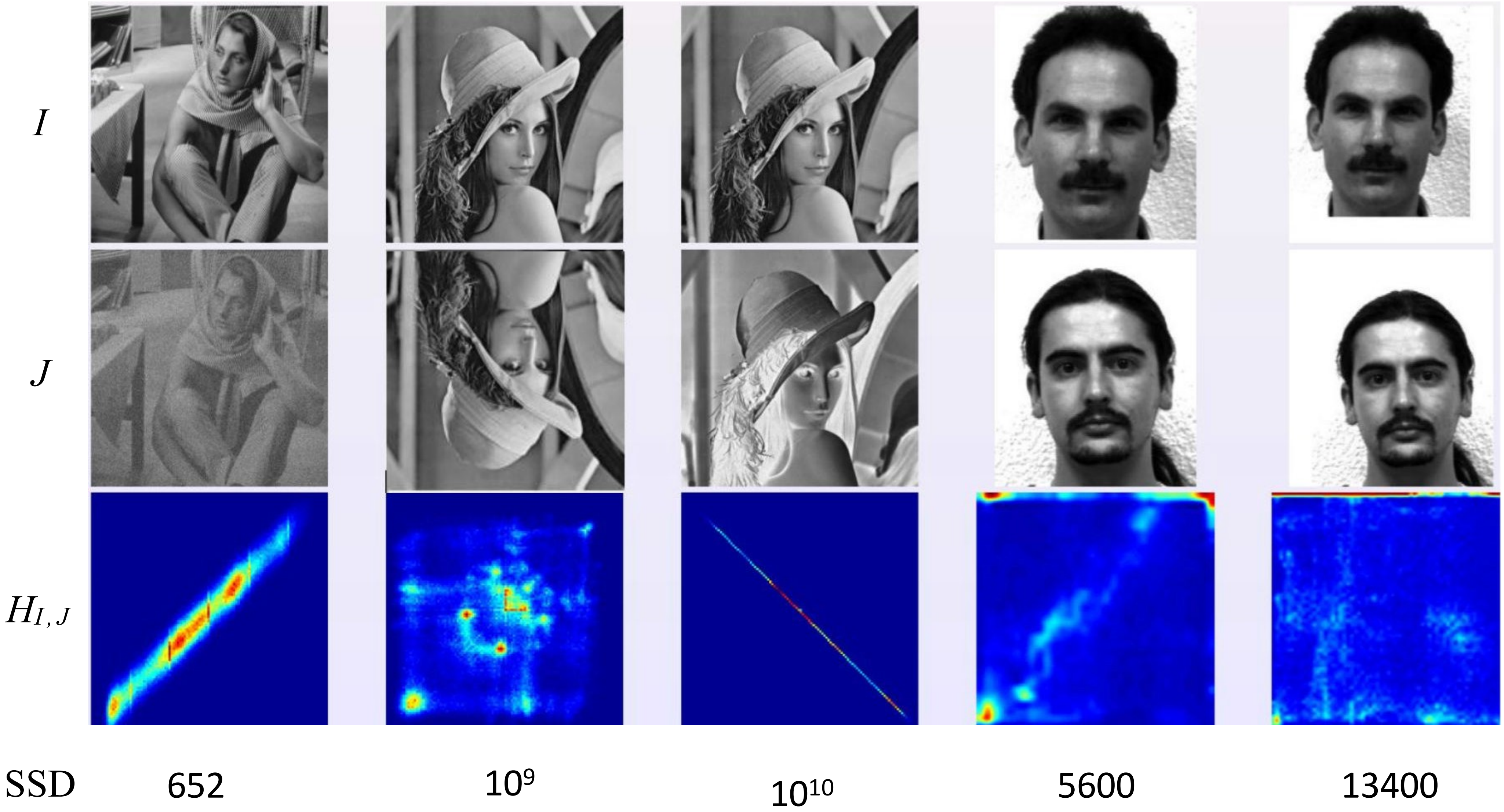
Notes

- NCC(I,J)∈[-1,1] ∀I,J. NCC(I,J)=0 ➜ no correlation
- Can be computed from $H_{I,J}$
- Have to be *maximized*
- Model *contrast differences*, only if linearly dependent



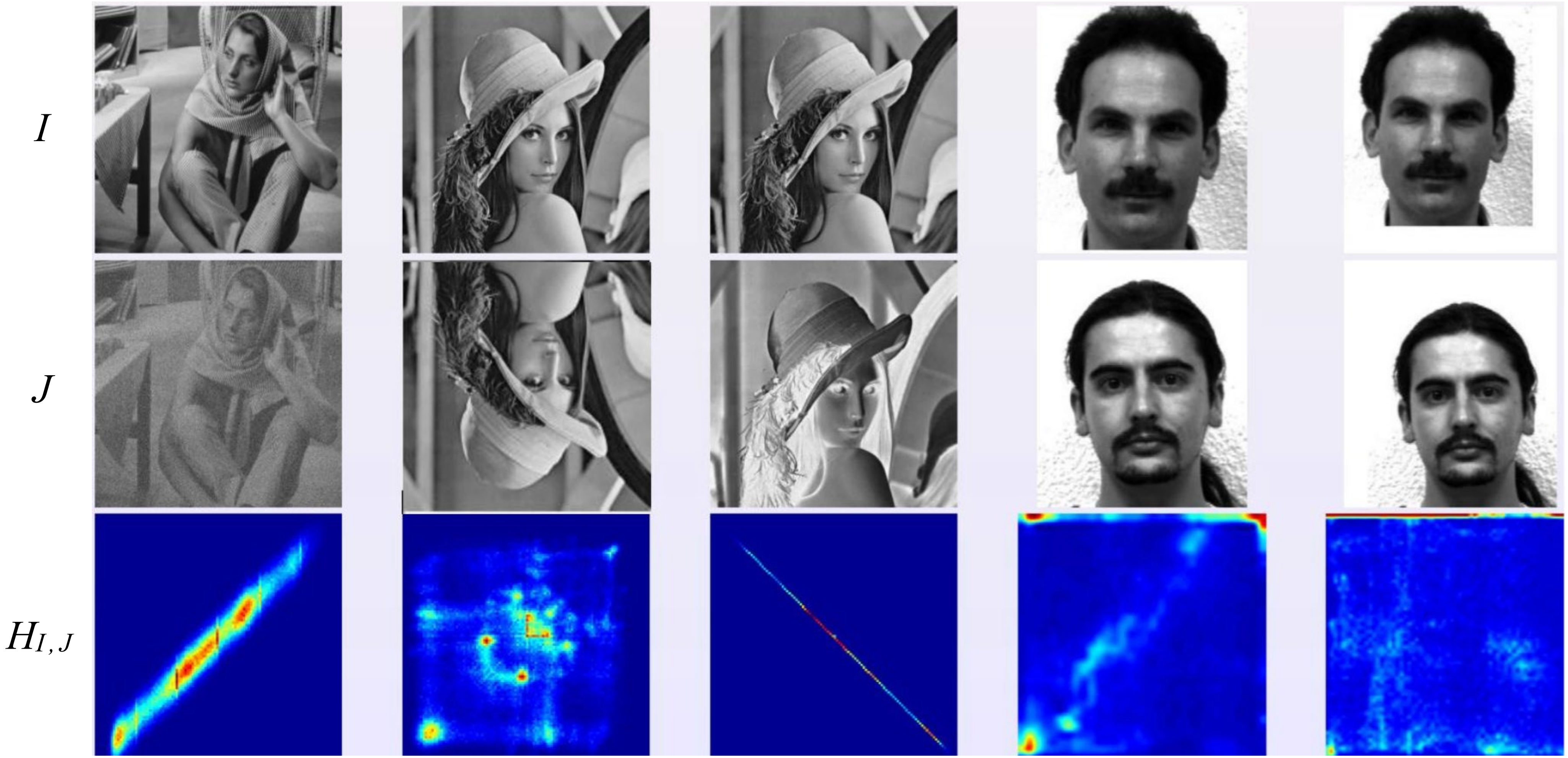
II - Similarity measures

SSD vs NCC



II - Similarity measures

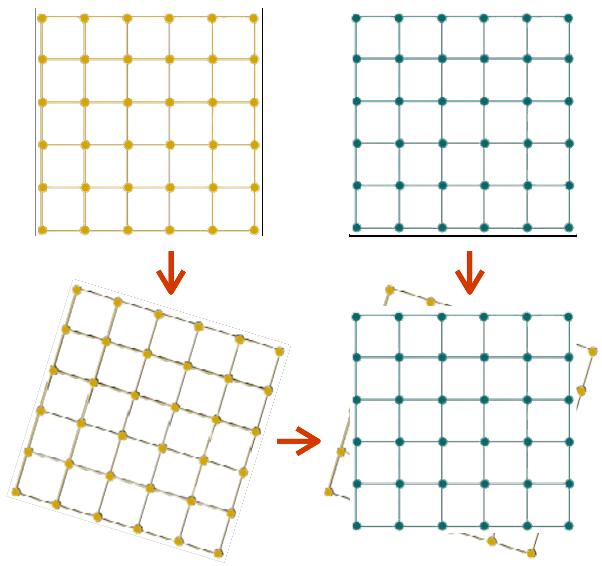
SSD vs NCC



NCC	0.95	-0.16	-1	0.54	0.14

III - Interpolators

- To compute distance/similarity $d(A, B^{\mathcal{T}})$ we need to compare features/ intensities at **same locations on both images**
  - If $\mathcal{T}$ maps the pixels of B exactly at the same locations of the pixels of A, there are no problems
  - But usually the locations/grids do not match



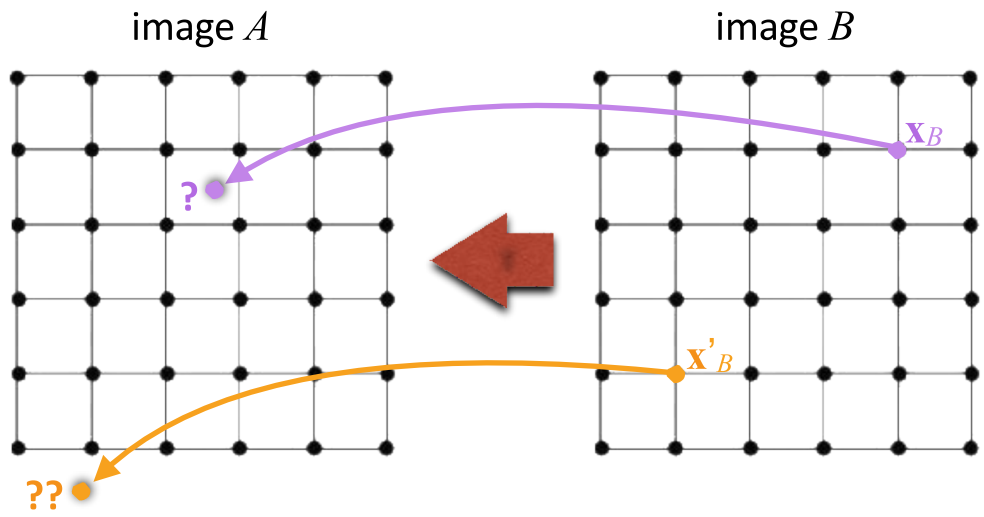
- Two cases
  - **Interpolation**

    -For the points $\mathbf{T}(\mathbf{x}_B)$ falling *inside* the grid of A (but not on the grid points themselves)

    -Value for these points needs to be estimated from the *neighboring pixels*
  - **Extrapola.on**

    -For the points $\mathbf{T}(\mathbf{x}_B)$ falling *outside* the grid of A

    -Points not considered? Mirror or extend pixels?

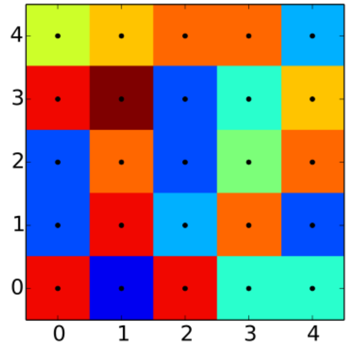


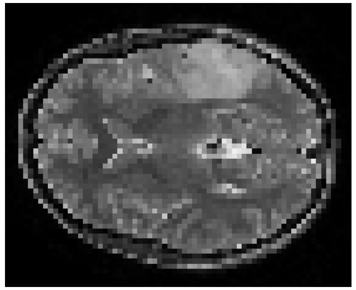
III - Interpolators

- Most common choices
  - **Nearest neighbor**

1D

2D

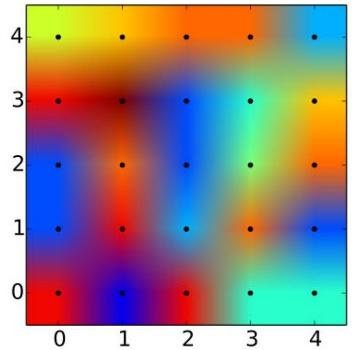


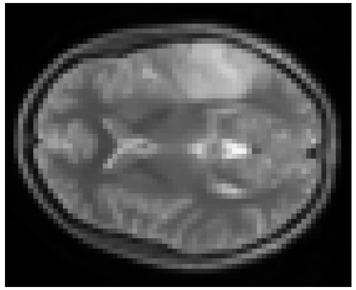


  - **Linear**

1D

2D

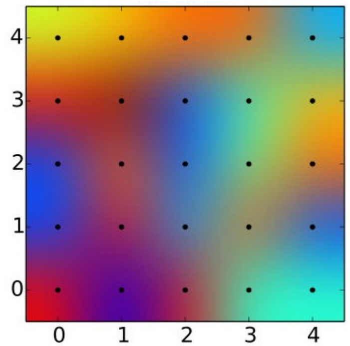


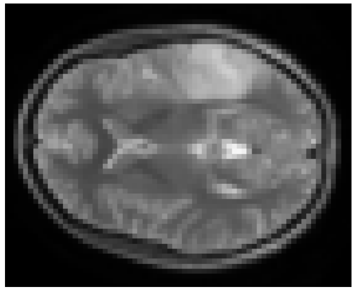


  - **Higher order**, e.g. cubic or B-spline

1D

2D





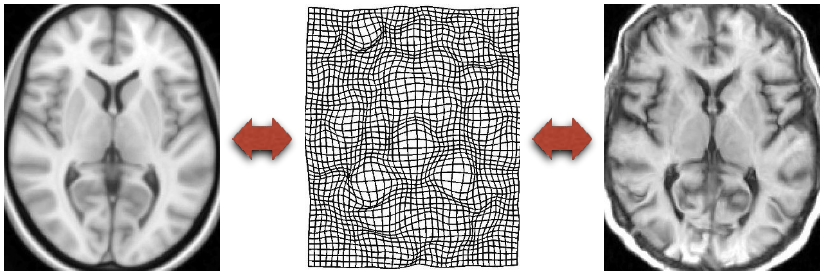
IV - Deforma. on models

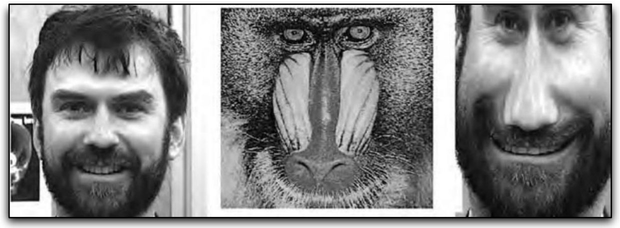
Two main categories

- **Linear** (a.k.a. *rigid*)
  - Only a limited number of *degrees of freedom* is allowed

$$\begin{pmatrix} \cos\beta\cos\gamma & \cos\alpha\sin\gamma+\sin\alpha\sin\beta\cos\gamma & \sin\alpha\sin\gamma-\cos\alpha\sin\beta\cos\gamma & t_x \\ -\cos\beta\sin\gamma & \cos\alpha\cos\gamma-\sin\alpha\sin\beta\sin\gamma & \sin\alpha\cos\gamma+\cos\alpha\sin\beta\sin\gamma & t_y \\ \sin\beta & -\sin\alpha\cos\beta & \cos\alpha\cos\beta & t_z \\ 0 & 0 & 0 & 1 \end{pmatrix}\begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}$$

- **Non-linear** (a.k.a. *non-rigid*)
  - Virtually any transforma5on/deforma5on is possible





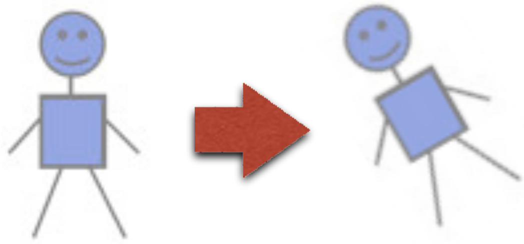
NB: the **choice of the deformation model** to use depends on the application, i.e. which tissue/structure to register

- *Bones of the skull* restrict the movement of the brain
  - *SoS 5ssue* tends to deform in more complicated ways

IV - Deforma. on models

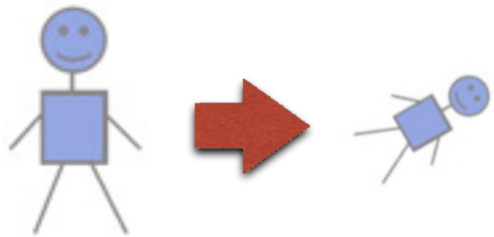
Linear transforma.ons

- **Rigid :** $\mathbf{T}(\mathbf{x}) = \mathbf{R}\mathbf{x} + \mathbf{t}$



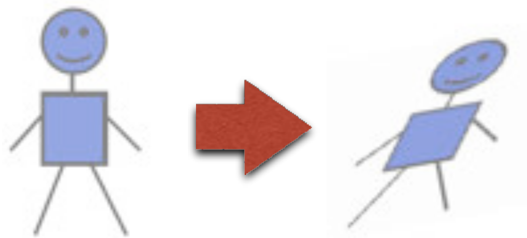
-**6 parameters** : rota5on ($\mathbf{R}$) and transla5on ($\mathbf{t}$)
-*Invariants*: distances (isometric), curvature, angles, lines
-*Use*: same structure in a different posi5on

- **Similitude :** $\mathbf{T}(\mathbf{x}) = \mathbf{s}\mathbf{R}\mathbf{x} + \mathbf{t}$



  - **7 parameters**: adds a scaling factor ($\mathbf{s}$)
  - *Invariants*: distance ra5os, angles, line

- **Affine :** $\mathbf{T}(\mathbf{x}) = \mathbf{A}\mathbf{x} + \mathbf{t}$



  - **12 parameters**: $\mathbf{A}$ includes stretching and shearing
  - *Invariants*: lines, parallelism
  - *Use*: - correct for scanner deforma5ons/ar5facts
  - find approximate alignment before nonlinear registra5on

IV - Deforma. on models

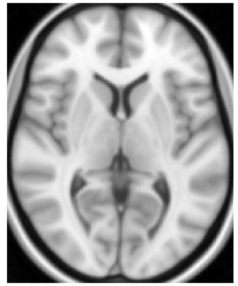
<u>**Nonlinear transformation**</u> required when registering:

- An image of one individual and **atlas**
  - Image from **different individuals**
- **Tissue that deforms** over time


5me 1


5me 2


subject


template

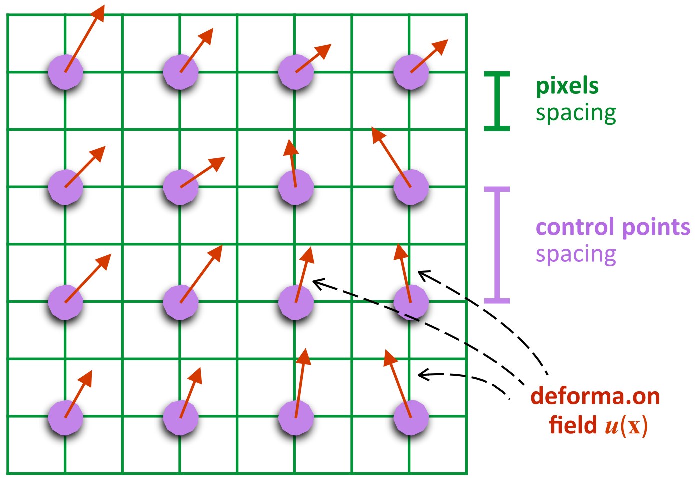
General approach

- **Each pixel** can virtually be moved independently

-One displacement per pixel

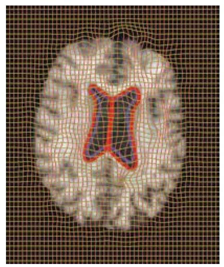
-Actual *tissue deformations* are usually more smooth/regular

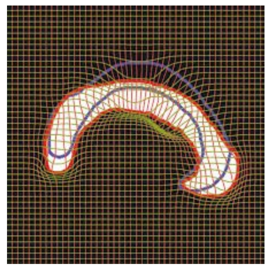
- Usually **grids of control points** are defined
  - One displacement $\boldsymbol{u}(\mathbf{x})$ ( ) per control point ( )
  - *Smoothness constraints* are usually added to obtain "anatomically reasonable" deforma5ons
  - Control points are *not independent*



- Several solutions **inspired by physics**
  - *Elastic*, *viscous fluid*, *op5cal flow*, *diffusion model* (demons)

    …

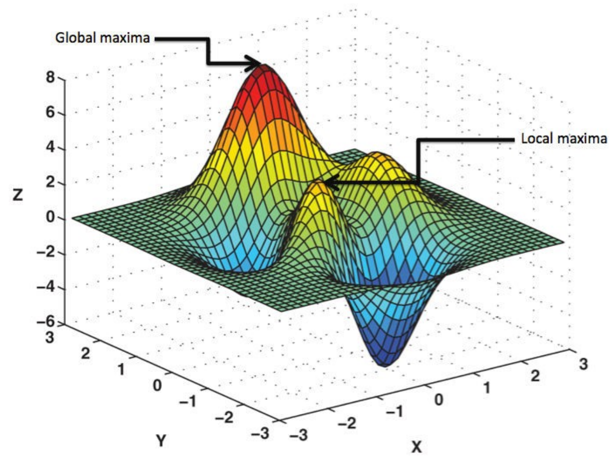




V - Optimizers

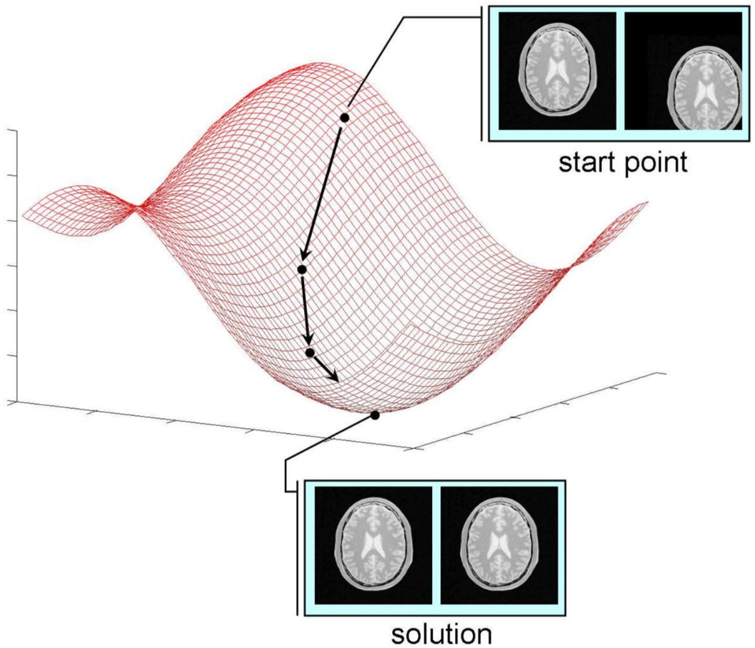
Registration is an **optimization problem**

- The search space is **high dimensional**
  (i.e. space of all possible transforma5ons)
- The problem is **nonlinear**
  (possibly with many **local minima**)



Usually **iterative approaches** are used

- Start with *initial estimate* of transformation, $\mathbf{T}^0$
- At each iteration *t*, current estimate $\mathbf{T}^t$ is used to compute a *similarity measure* $d(A, B^{\mathcal{T}})$
- Using d, *refine the transforma5on* $\mathbf{T}^t \rightarrow \mathbf{T}^{t+1}$
- Continues until the convergence

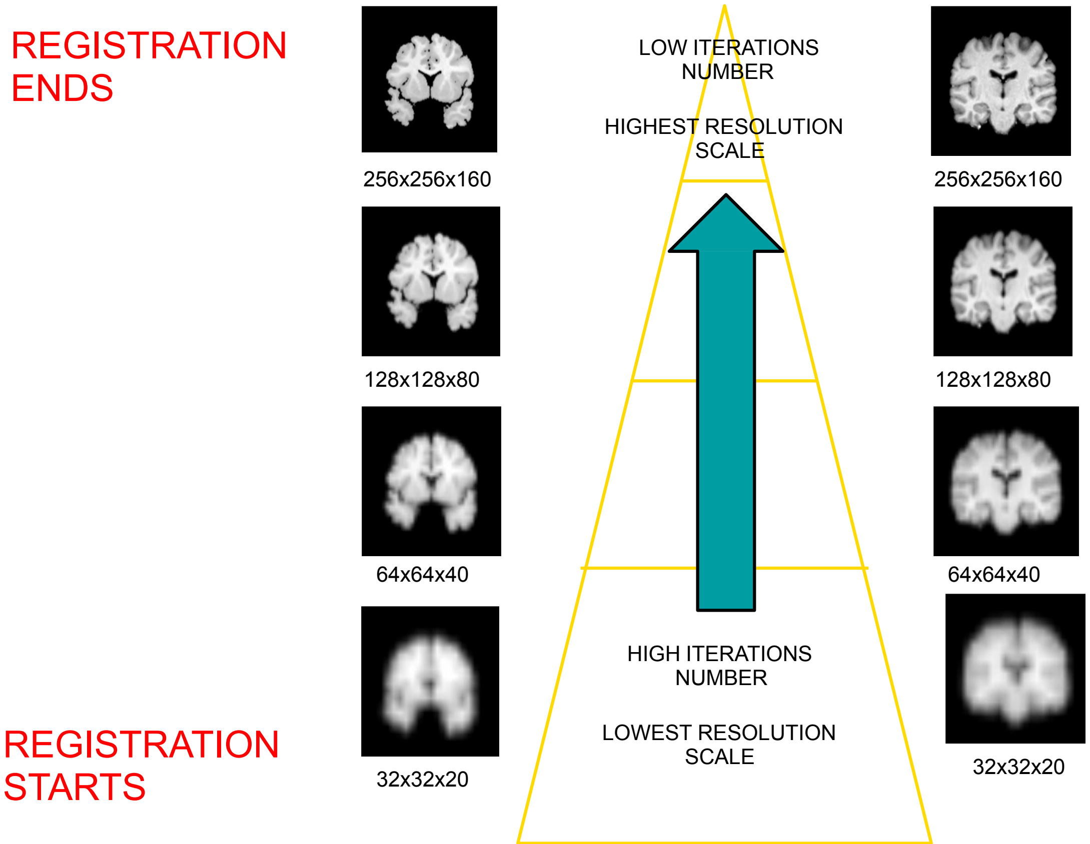


Classical algorithms

- *Gauss-Newton, (stochas5c) gradient descent* etc…

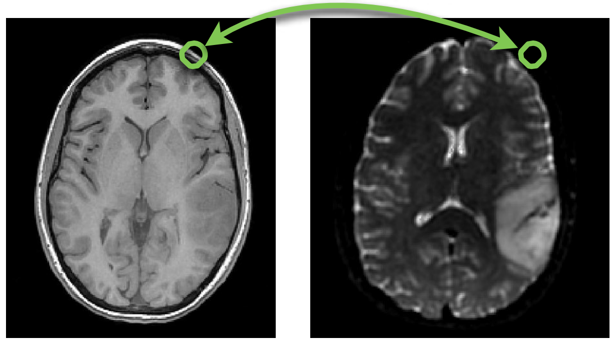
Mul. -scale pyramid

- Strategy to improve **registration accuracy**
  - Start the registration using **images with low complexity** → *smoothing*, *downsampling*
  - At convergence, **increase the complexity/details of the images** and repeat
  - This reduces the chance of falling in **local minima** (bad registra5on)



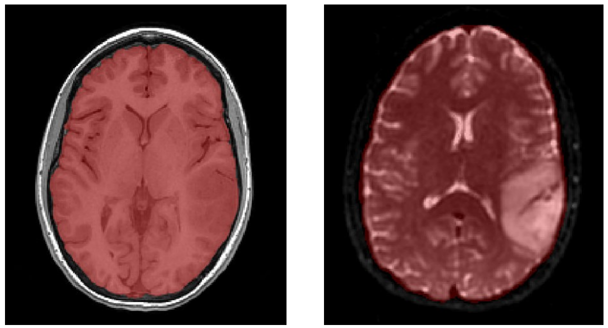
Use of masks

- Sometimes it is desirable to **align only part of an image**
  - We are interested **only on a por.on or some details** of the image
    - We need to **ignore parts of the images** that can confound the registra5on (e.g. *ar5ficial edges*)



Some anatomical details are not visible in both images

- With a mask registration is **constrained to a region**



- A mask is a **binary image**
  - “**1**” ➡ the pixel in
  - *considered*
    “**0**” ➡ the pixel in *ignored*
- A **fixed image mask is usually sufficient** to focus the registration on a region, since samples are drawn from the domain of the fixed image

Available tools

- ITK.org : MITK, MedINRIA, Slicer3D,
- etc Elastix
  Choice for our lab: **power of ITK** (all algorithms) with **simple interface**
  -
- FSL FLIRT (linear) and FNIRT
- (nonlinear) ANTs (Advanced
- Normaliza5on Tools) SPM
- Freesurfer Hammer / Glirt
- BrainVisa / Anatomist and many
- others more....