Landmark-based Registration

Aalto-yliopisto
Aalto-universitetet
Aalto University

Medical Image Analysis

Koen Van Leemput

Fall 2024

Image registration

Combine information contained in different scans

Images need to be spatially aligned!

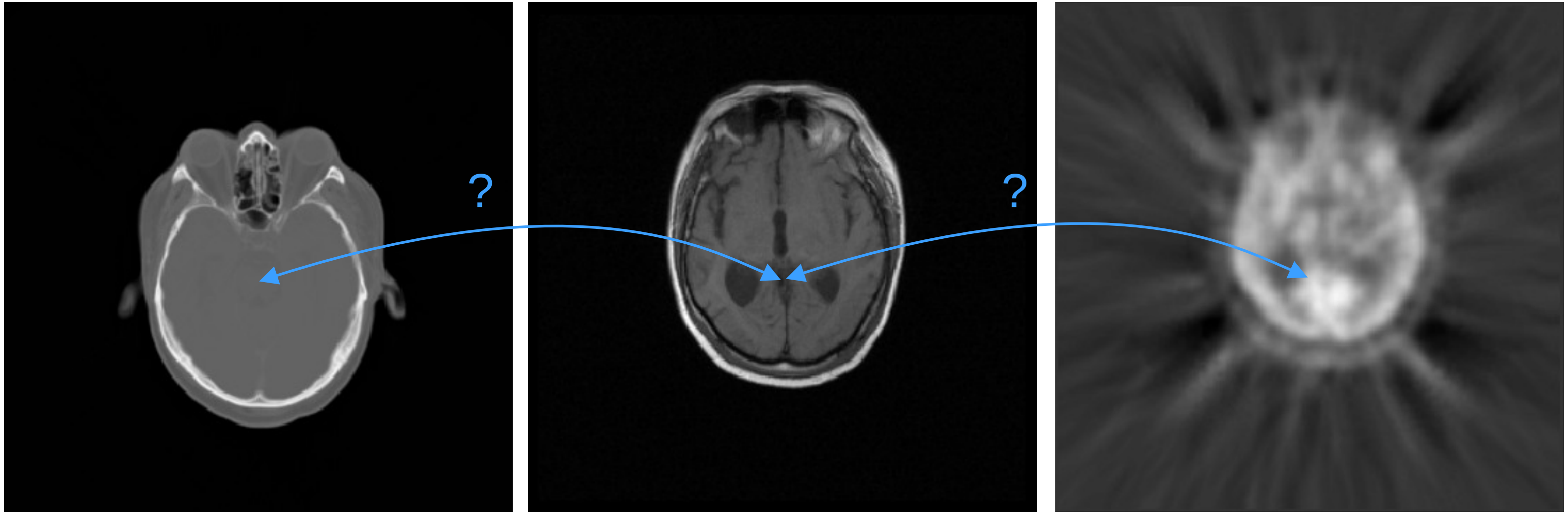

Image registration

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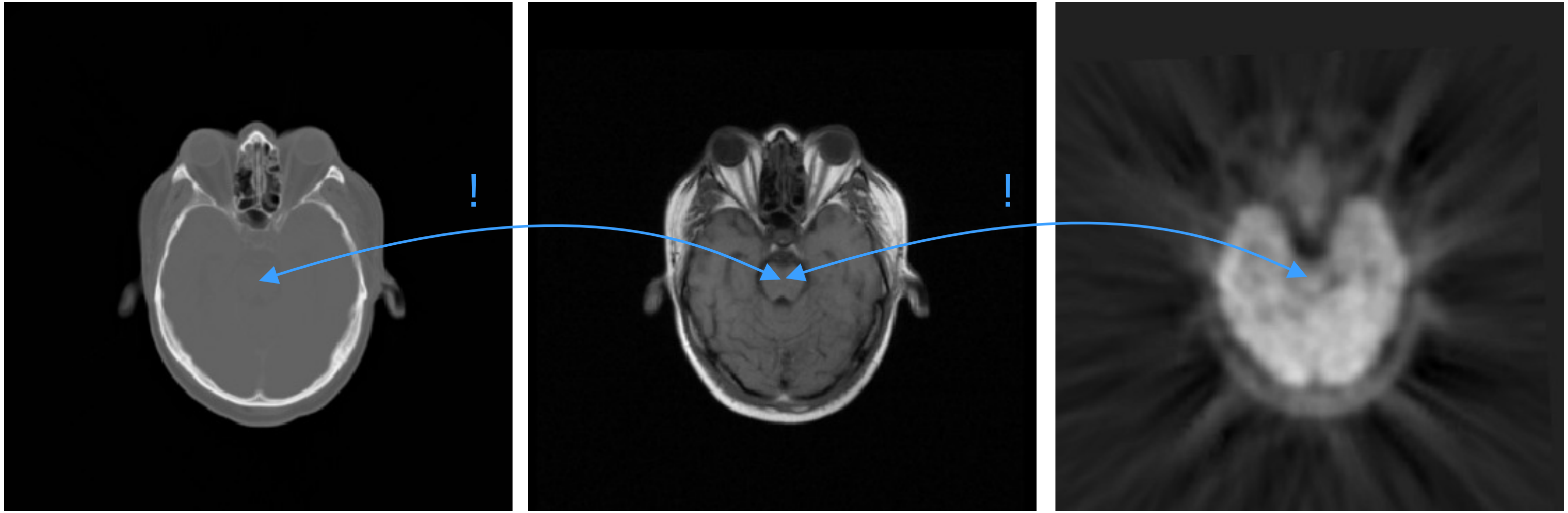
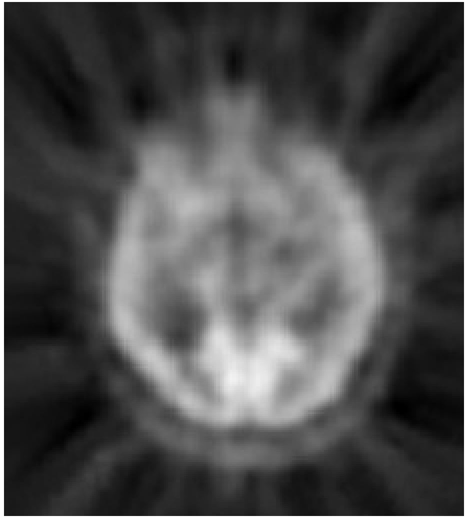
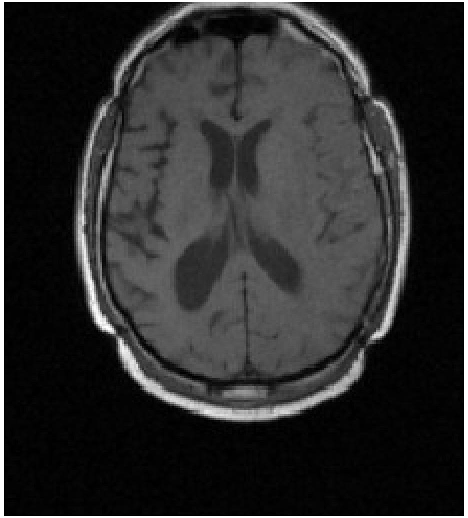
Images need to be spatially aligned!



Example: PET/MR

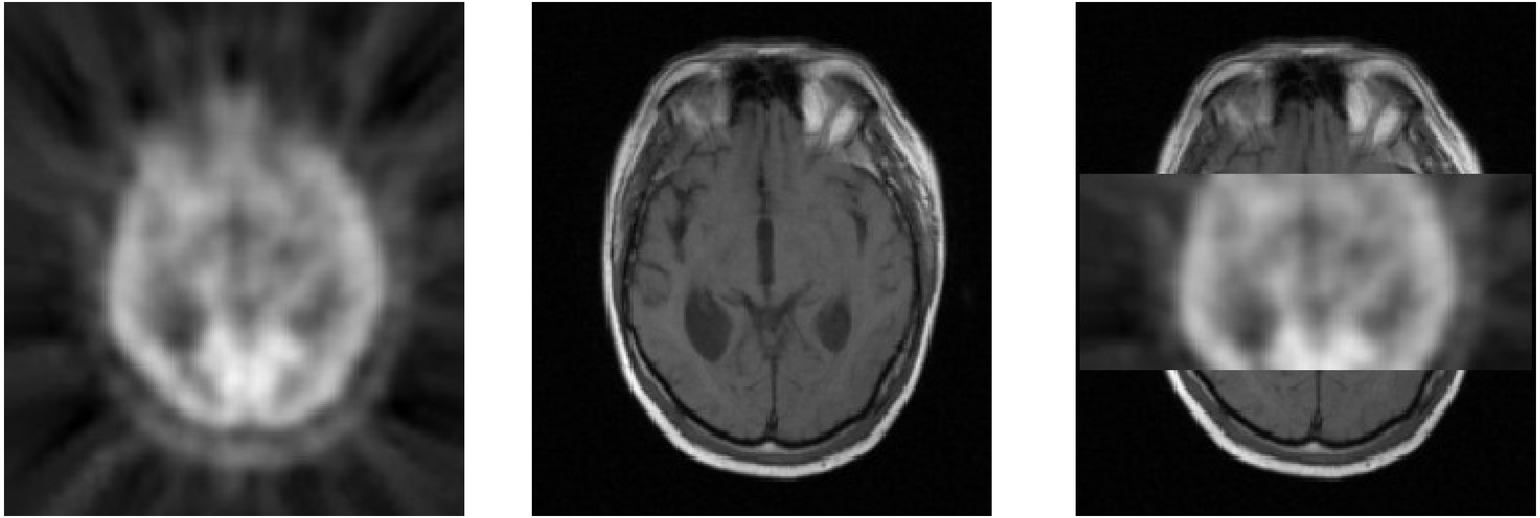
Before registration...





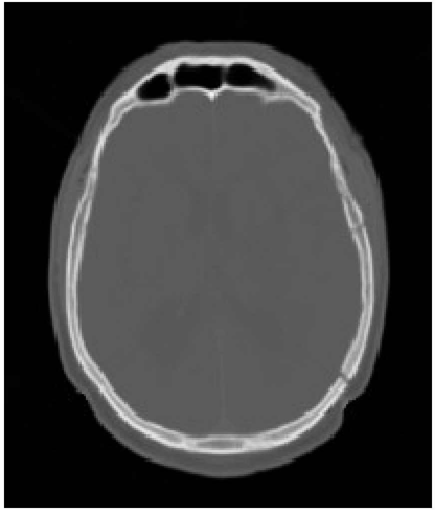
Example: PET/MR

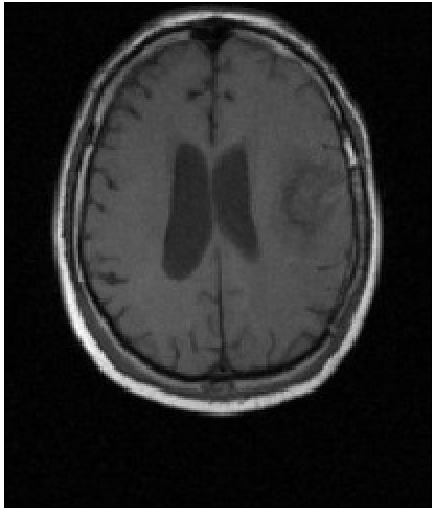
… after registration



Example: CT/MR

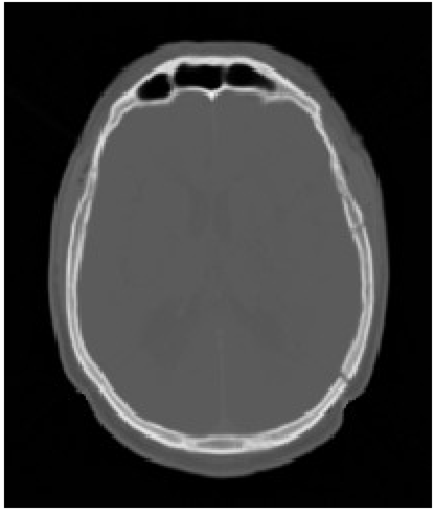
Before registration…

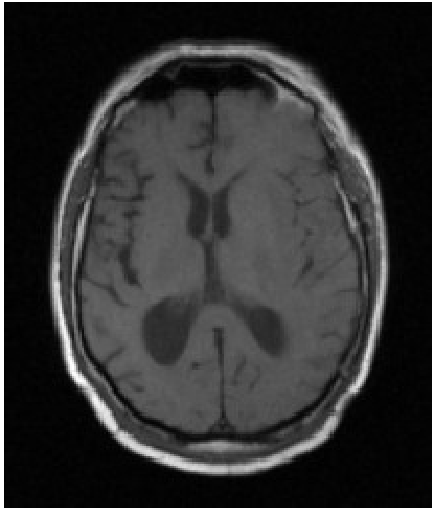




Example: CT/MR

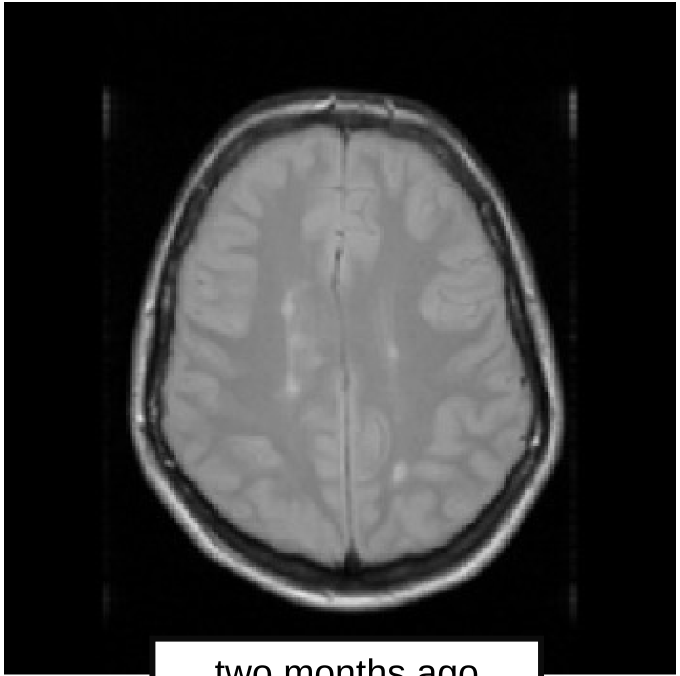
… after registration





Example: longitudinal scans

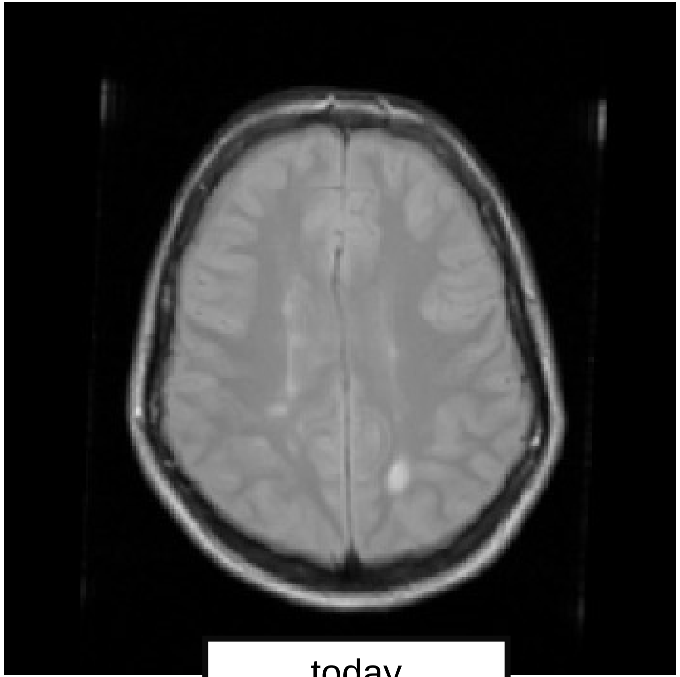
Patient with multiple sclerosis (MS)



two months ago

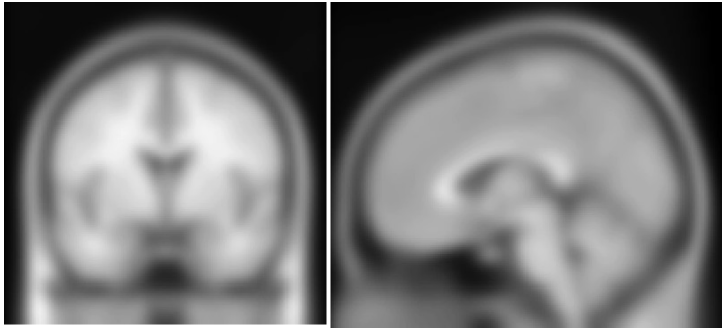
Example: longitudinal scans

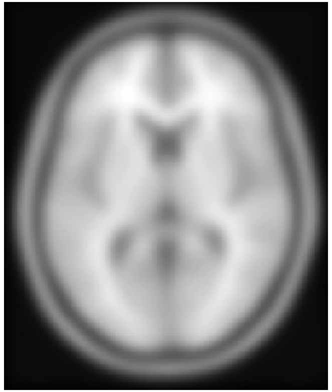
Patient with multiple sclerosis (MS)



today

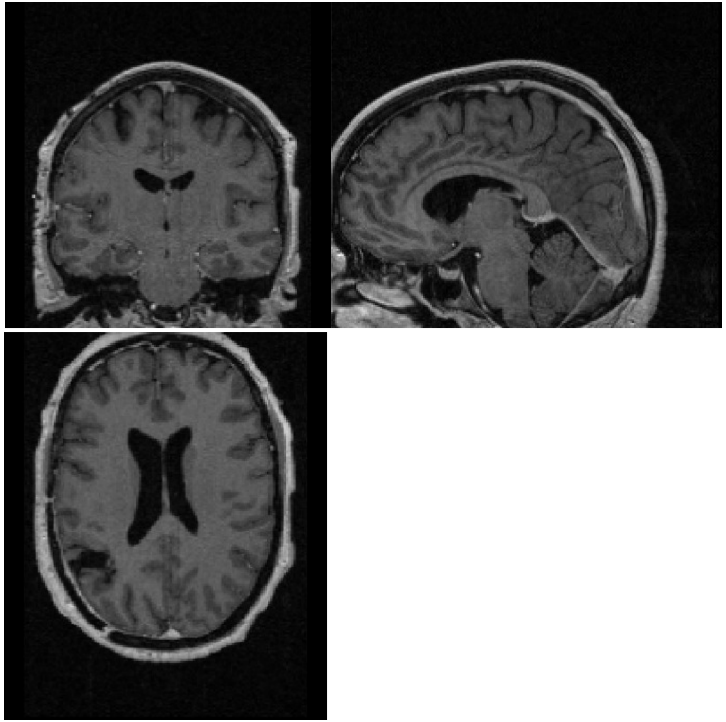
Example: population studies



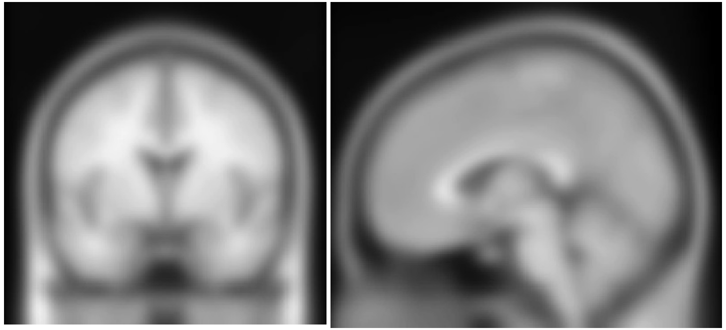


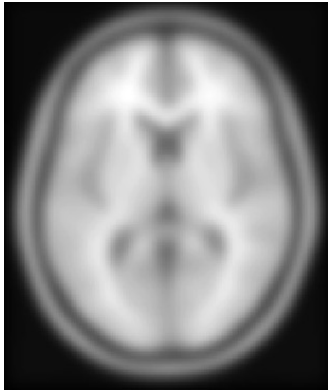
average of 152 individuals

International Consortium for Brain Mapping



Example: population studies





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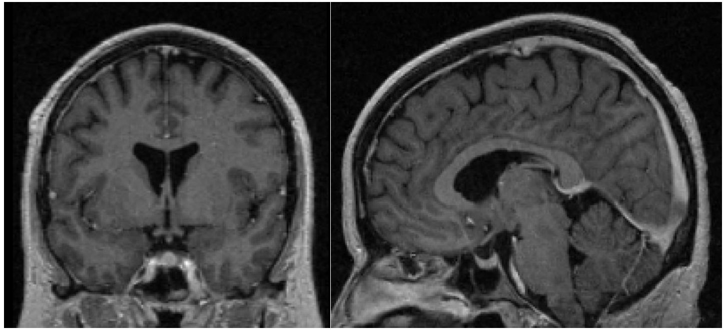
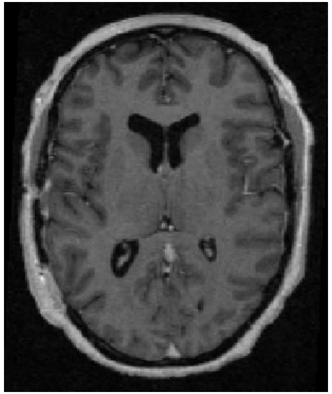
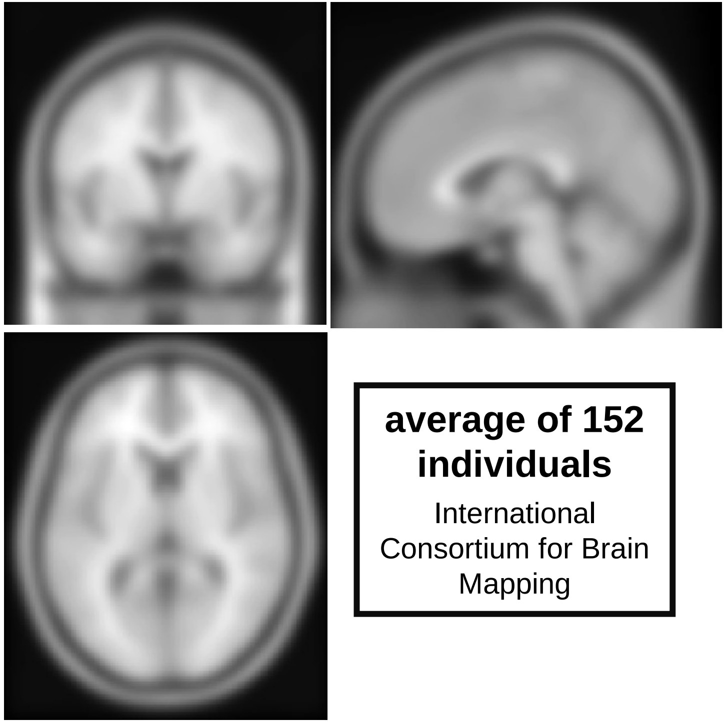




Example: population studies



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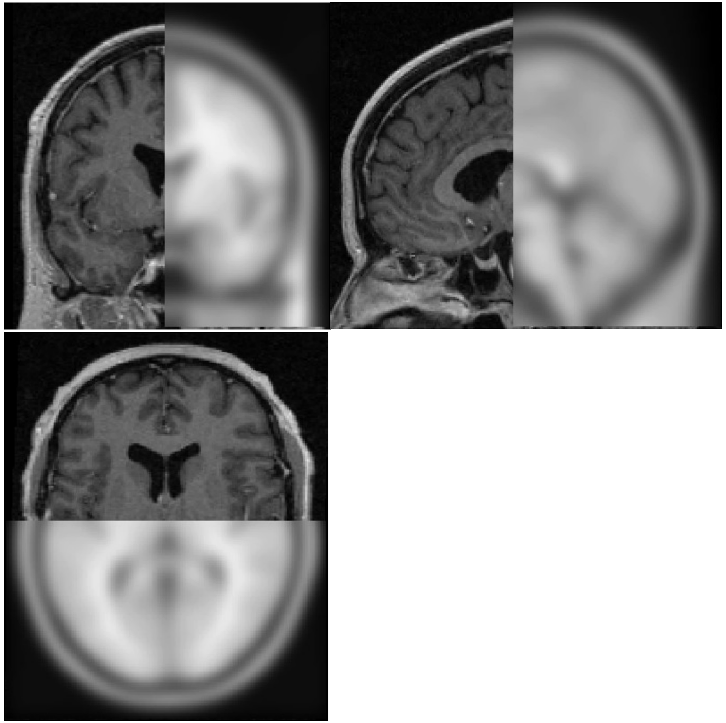

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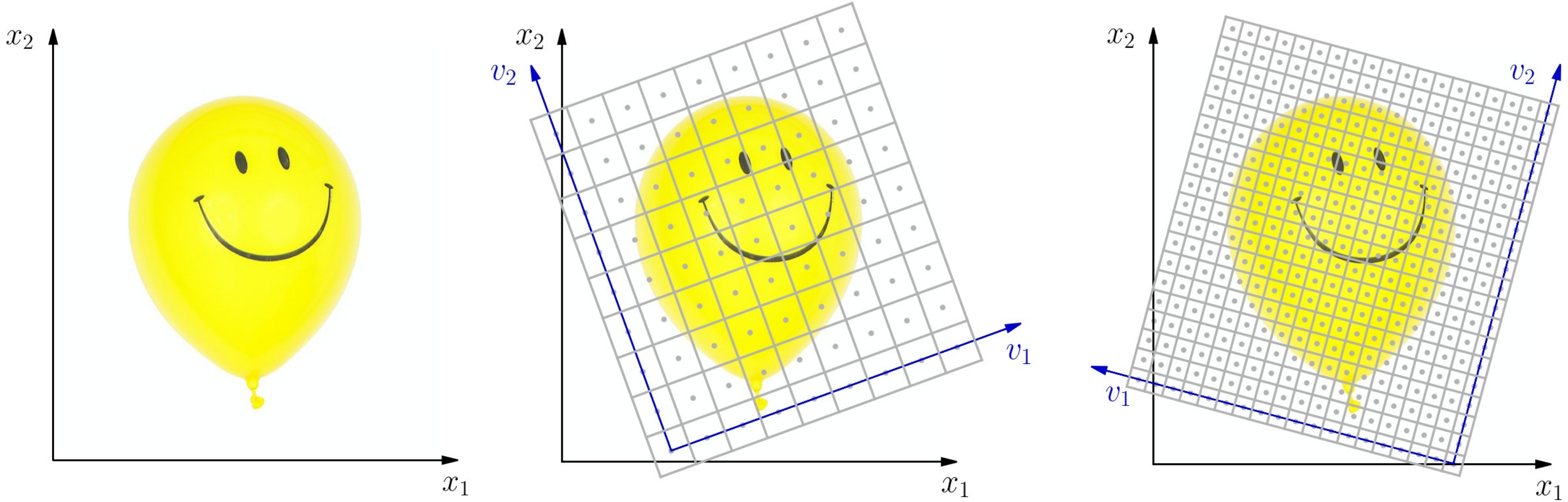
Coordinate systems

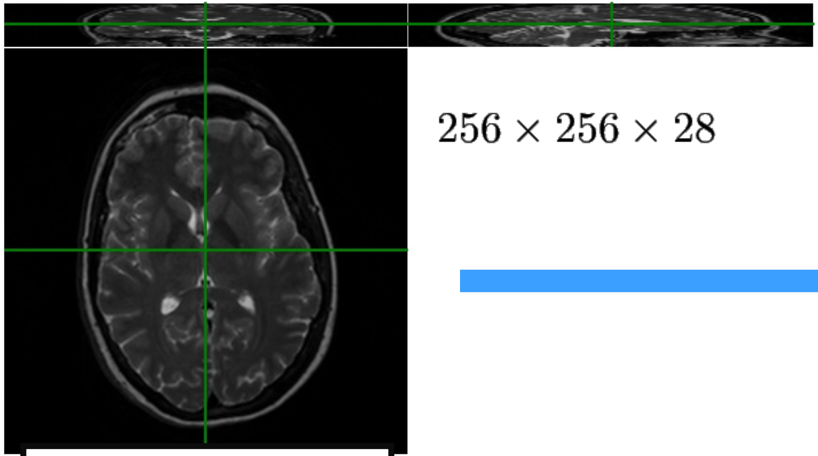
For each image, there are *<u>two</u>* coordinate systems:

- ✔ Voxel coordinates $\mathbf{v} = (v_1, v_2, v_3)^{\mathrm{T}}$ *(integer indices)*
- ✔ World coordinates $\mathbf{x} = (x_1, x_2, x_3)^{\mathrm{T}}$ *(in mm)*



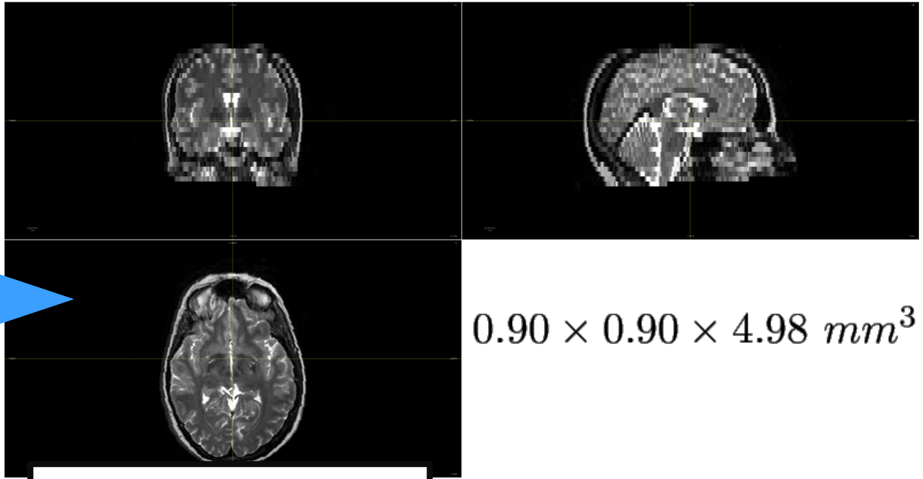
Conversion: $\mathbf{x} = \mathbf{A}\mathbf{v} + \mathbf{t}$

Coordinate systems



$256 \times 256 \times 28$

voxel indices $\mathbf{v}$



$0.90 \times 0.90 \times 4.98 \; mm^3$

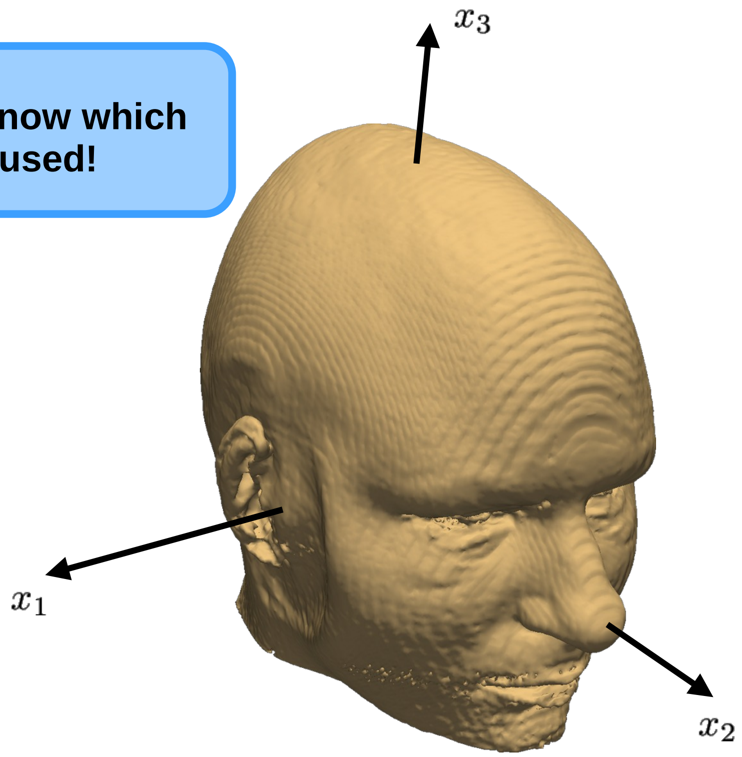
world positions $\mathbf{x}$

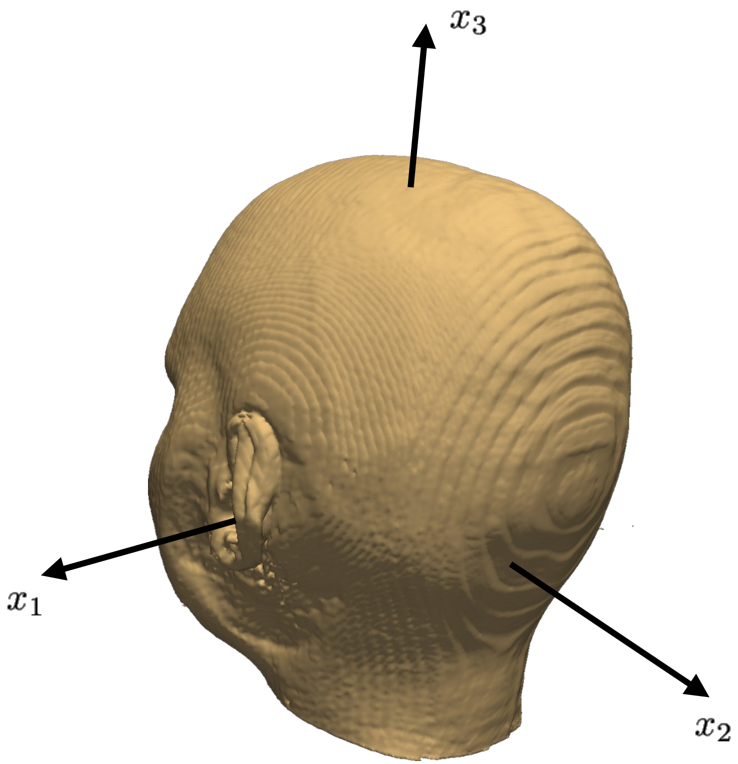
Conversion: $\mathbf{x} = \mathbf{A}\mathbf{v} + \mathbf{t}$

$$\mathbf{A} = \begin{pmatrix} -0.8923 & -0.0802 & -0.3732 \\ -0.0850 & 0.8921 & 0.3528 \\ -0.0612 & -0.0696 & 4.9512 \end{pmatrix} \qquad \mathbf{t} = \begin{pmatrix} 129.2834 \\ -98.7363 \\ -27.6911 \end{pmatrix}$$

World coordinates = convention

Important to know which convention is used!





Right – Anterior – Superior (RAS)	Left – Posterior – Superior (LPS)

Homogeneous coordinates

Vectors are augmented with a 1 at the end

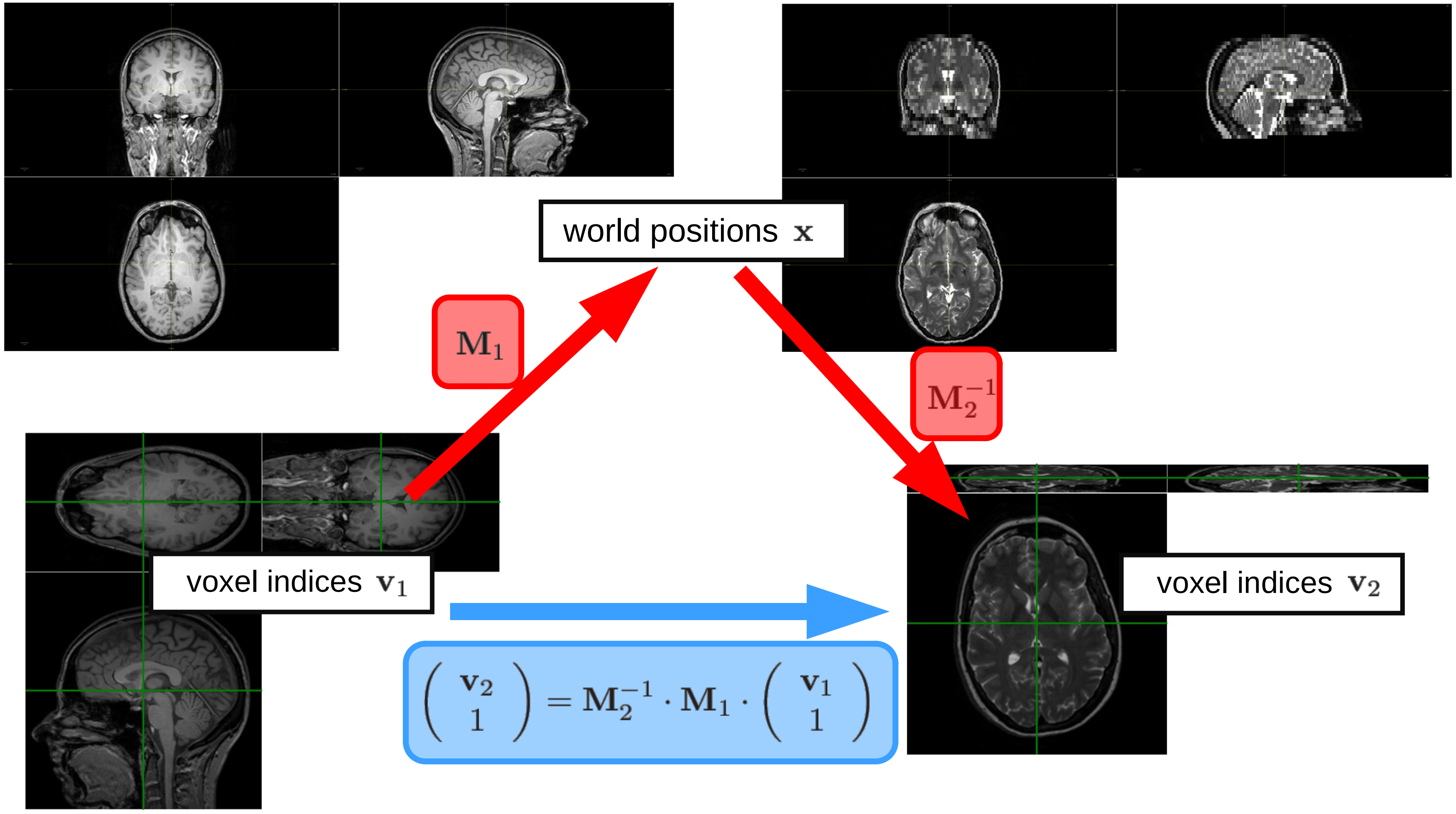
- ✔ **Idea:** Rewrite $\mathbf{x} = \mathbf{A}\mathbf{v} + \mathbf{t}$, i.e,

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \\ v_3 \end{pmatrix} + \begin{pmatrix} t_1 \\ t_2 \\ t_3 \end{pmatrix}$$

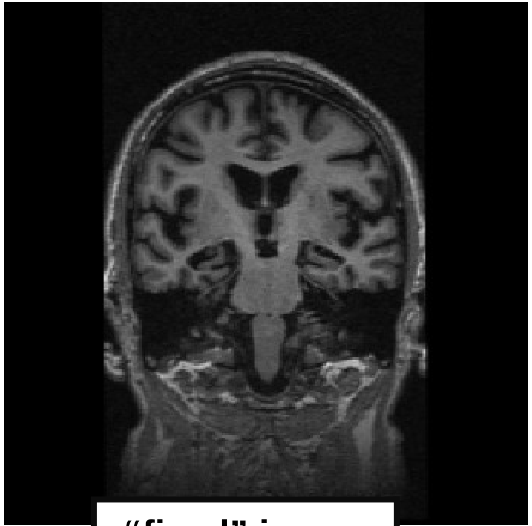
as:

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ 1 \end{pmatrix} = \underbrace{\begin{pmatrix} a_{1,1} & a_{1,2} & a_{1,3} & t_1 \\ a_{2,1} & a_{2,2} & a_{2,3} & t_2 \\ a_{3,1} & a_{3,2} & a_{3,3} & t_3 \\ 0 & 0 & 0 & 1 \end{pmatrix}}_{\mathbf{M}} \begin{pmatrix} v_1 \\ v_2 \\ v_3 \\ 1 \end{pmatrix}$$

- ✔ **Benefit:** map voxel indices using only matrix multiplications

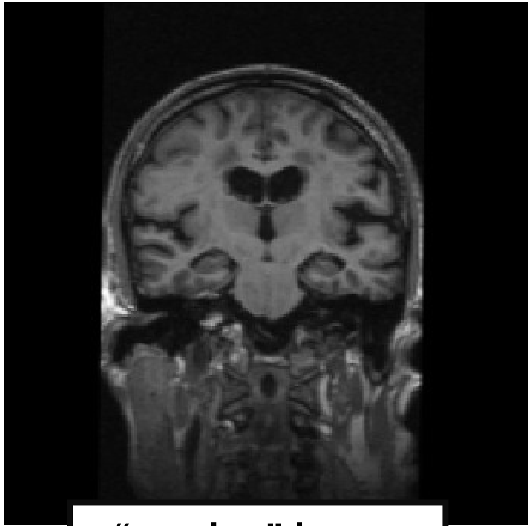

world positions $\mathbf{x}$
$\mathbf{M}_1$
$\mathbf{M}_2^{-1}$
voxel indices $\mathbf{v}_1$
voxel indices $\mathbf{v}_2$
$\begin{pmatrix} \mathbf{v}_2 \\ 1 \end{pmatrix} = \mathbf{M}_2^{-1} \cdot \mathbf{M}_1 \cdot \begin{pmatrix} \mathbf{v}_1 \\ 1 \end{pmatrix}$

Spatial transformations



“fixed” image

$$\mathbf{x} = (x_1, \ldots, x_D)^{\mathrm{T}}$$

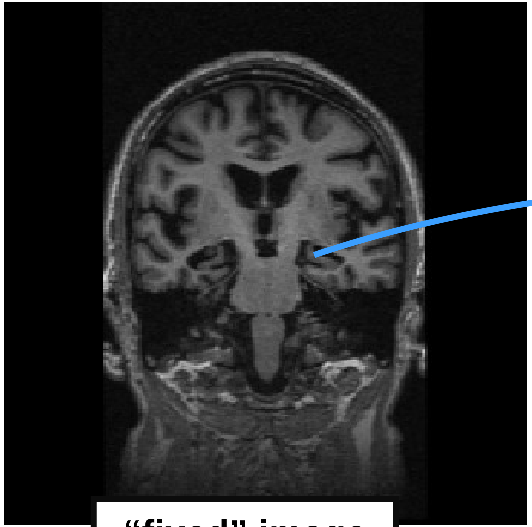


“moving” image

$$\mathbf{y} = (y_1, \ldots, y_D)^{\mathrm{T}}$$

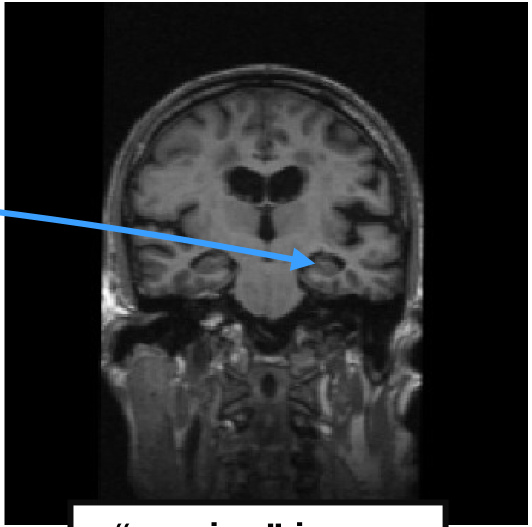
Spatial transformations

$$\mathbf{y}(\mathbf{x}, \mathbf{w}) = \begin{pmatrix} y_1(\mathbf{x}, \mathbf{w}) \\ \vdots \\ y_D(\mathbf{x}, \mathbf{w}) \end{pmatrix}$$



“fixed” image

$$\mathbf{x} = (x_1, \ldots, x_D)^{\mathrm{T}}$$



“moving” image

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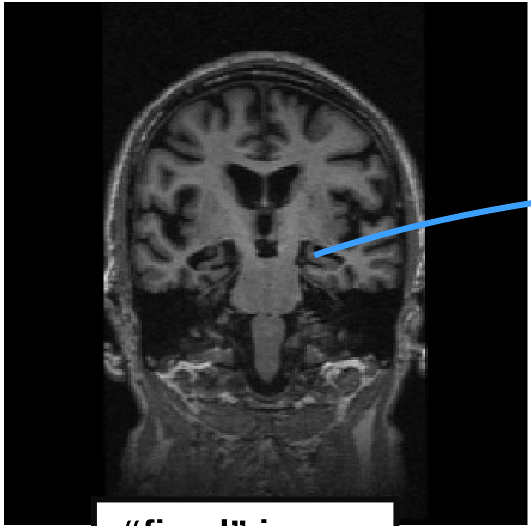

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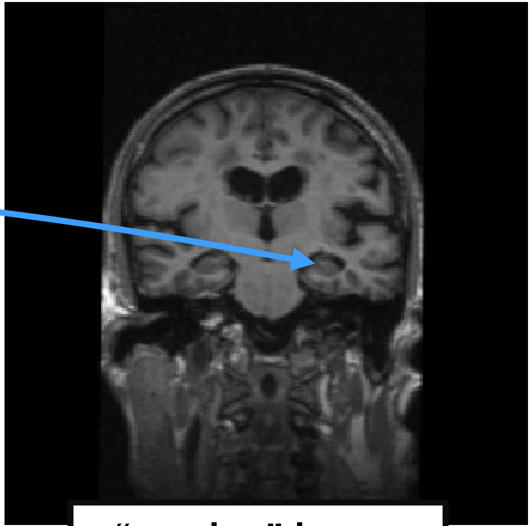
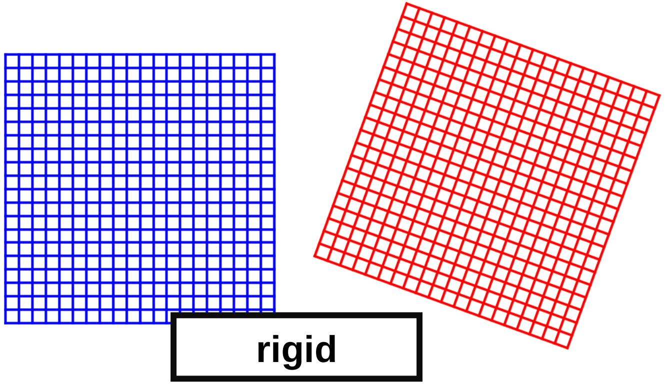


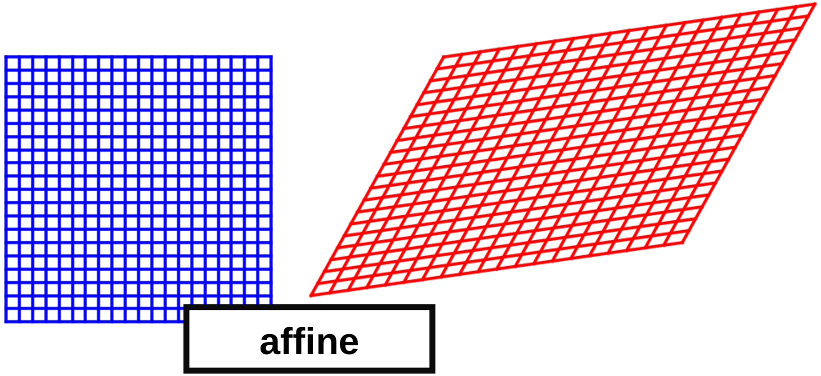
“moving” image

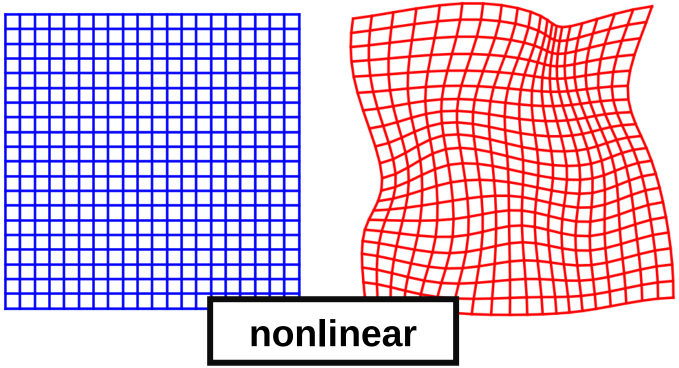
$\mathbf{y} = (y_1, \ldots, y_D)^{\mathrm{T}}$

$y_d(\mathbf{x},\mathbf{w})$
controls how points $\mathbf{x}$ in the fixed image
move along the d-th direction in the moving image
as the parameters $\mathbf{w}$ are varied

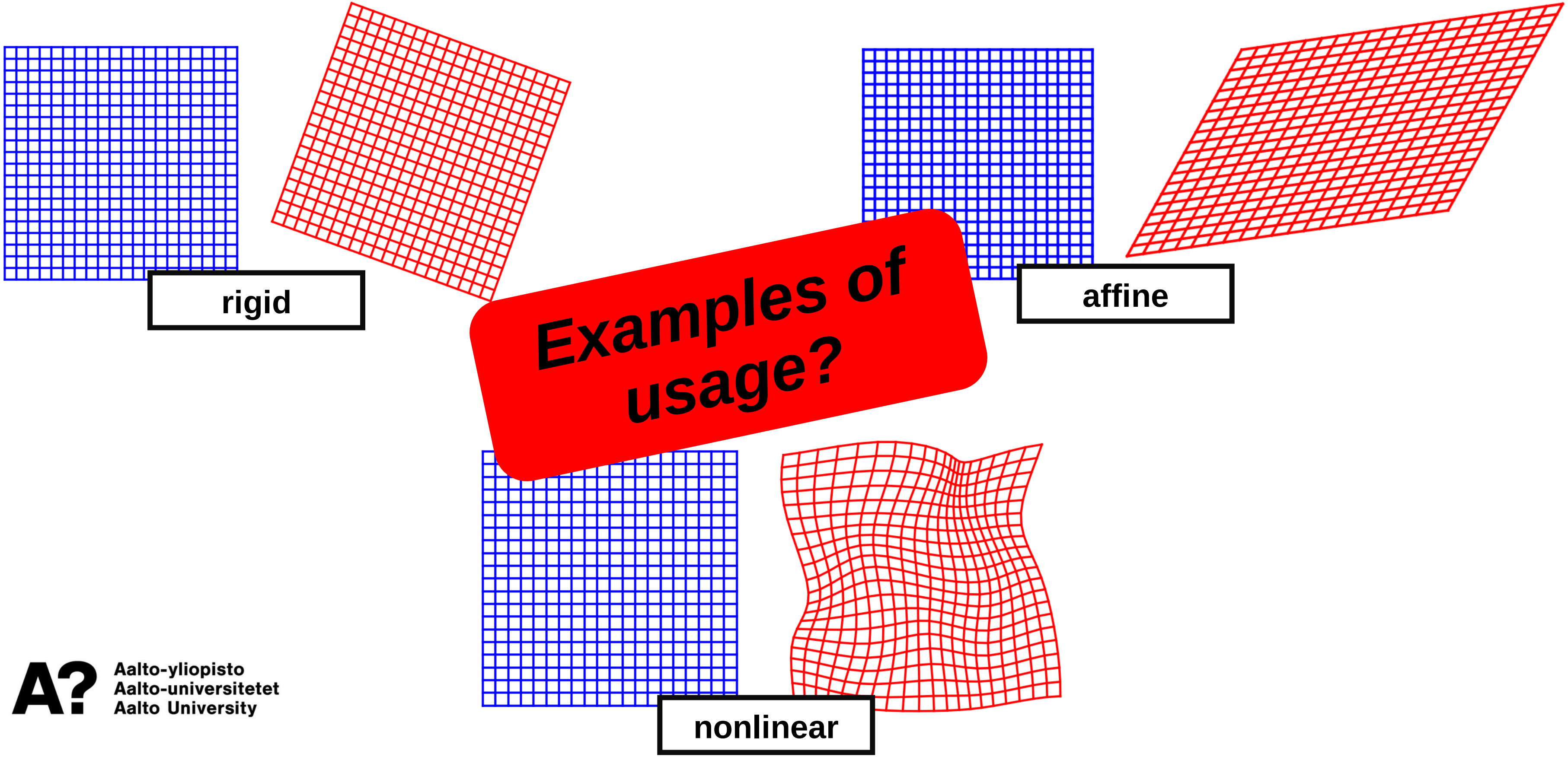
Spatial transformations







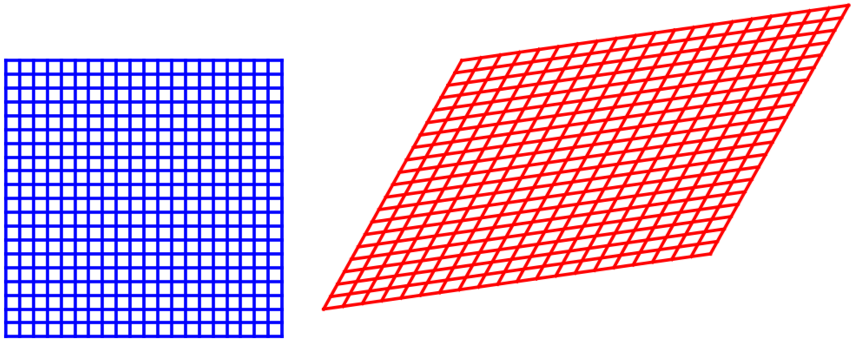
Spatial transformations



Affine transformation

$$\mathbf{y}(\mathbf{x}, \mathbf{w}) = \mathbf{A}\mathbf{x} + \mathbf{t}$$

$$\mathbf{A} = \begin{pmatrix} a_{1,1} & a_{1,2} \\ a_{2,1} & a_{2,2} \end{pmatrix} \quad \text{and} \quad \mathbf{t} = \begin{pmatrix} t_1 \\ t_2 \end{pmatrix}$$



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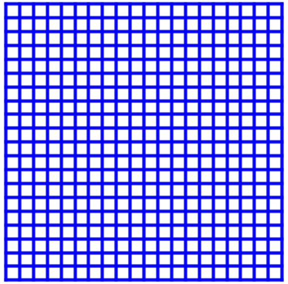
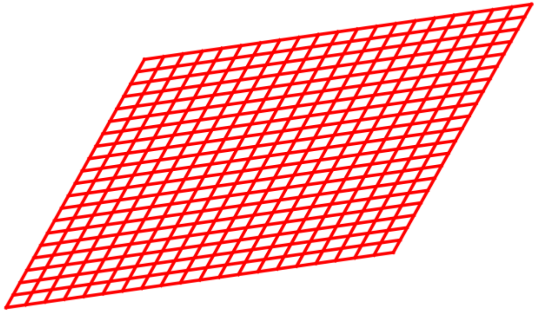




$y_d(\mathbf{x}, \mathbf{w})$
controls how points $\mathbf{x}$ in the fixed image
move along the d-th direction in the moving image
as the parameters $\mathbf{w}$ are varied

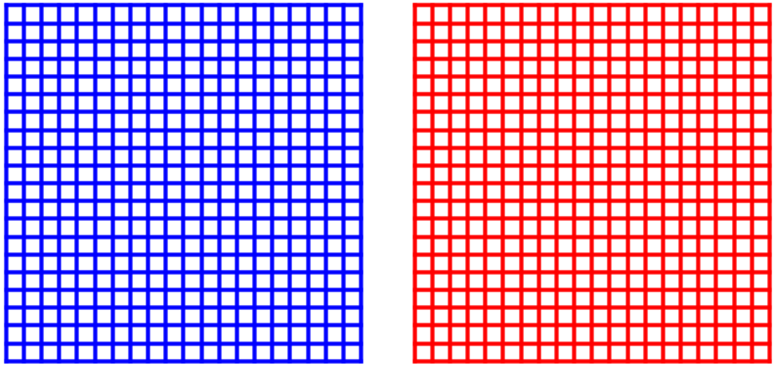
$$y_d(\mathbf{x}, \mathbf{w}_d) = t_d + a_{d,1}x_1 + \ldots + a_{d,D}x_D$$

$$\mathbf{w}_d = (t_d, a_{d,1}, \ldots, a_{d,D})^{\mathrm{T}}$$

$$\mathbf{w} = (\mathbf{w}_1^{\mathrm{T}}, \ldots, \mathbf{w}_D^{\mathrm{T}})^{\mathrm{T}}$$

Affine transformation

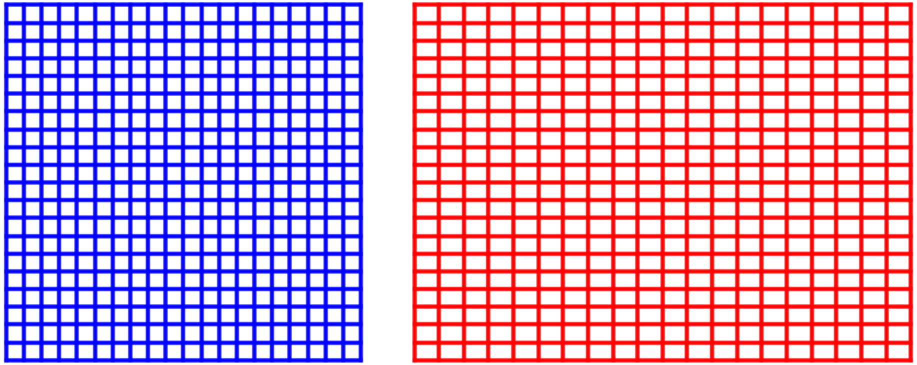
$$\mathbf{y}(\mathbf{x}, \mathbf{w}) = \mathbf{A}\mathbf{x} + \mathbf{t}$$



$$\mathbf{A} = \begin{pmatrix} 1.0 & 0.0 \\ 0.0 & 1.0 \end{pmatrix}, \quad \mathbf{t} = \begin{pmatrix} 23 \\ 0 \end{pmatrix}$$

Affine transformation

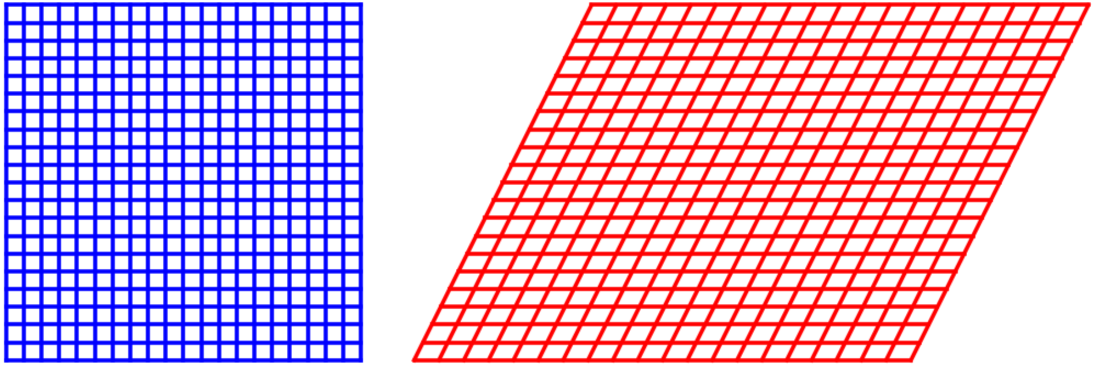
$$\mathbf{y}(\mathbf{x},\mathbf{w}) = \mathbf{A}\mathbf{x} + \mathbf{t}$$



$$\mathbf{A} = \begin{pmatrix} 1.4 & 0.0 \\ 0.0 & 1.0 \end{pmatrix}, \quad \mathbf{t} = \begin{pmatrix} 23 \\ 0 \end{pmatrix}$$

Affine transformation

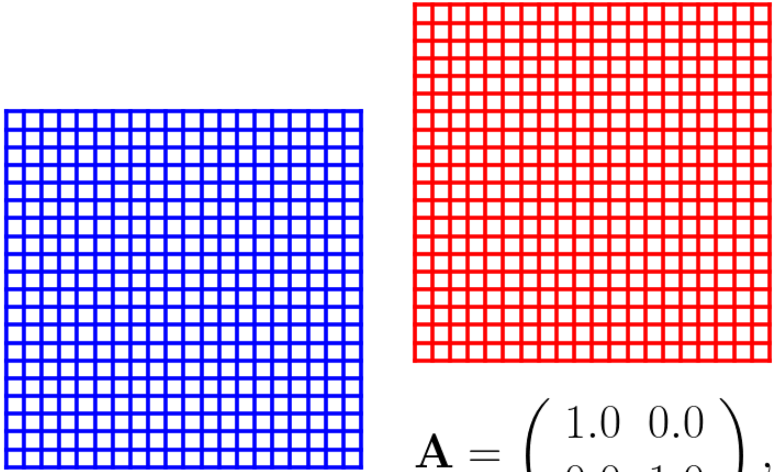
$$\mathbf{y}(\mathbf{x}, \mathbf{w}) = \mathbf{A}\mathbf{x} + \mathbf{t}$$



$$\mathbf{A} = \begin{pmatrix} 1.4 & 0.5 \\ 0.0 & 1.0 \end{pmatrix}, \quad \mathbf{t} = \begin{pmatrix} 23 \\ 0 \end{pmatrix}$$

Affine transformation

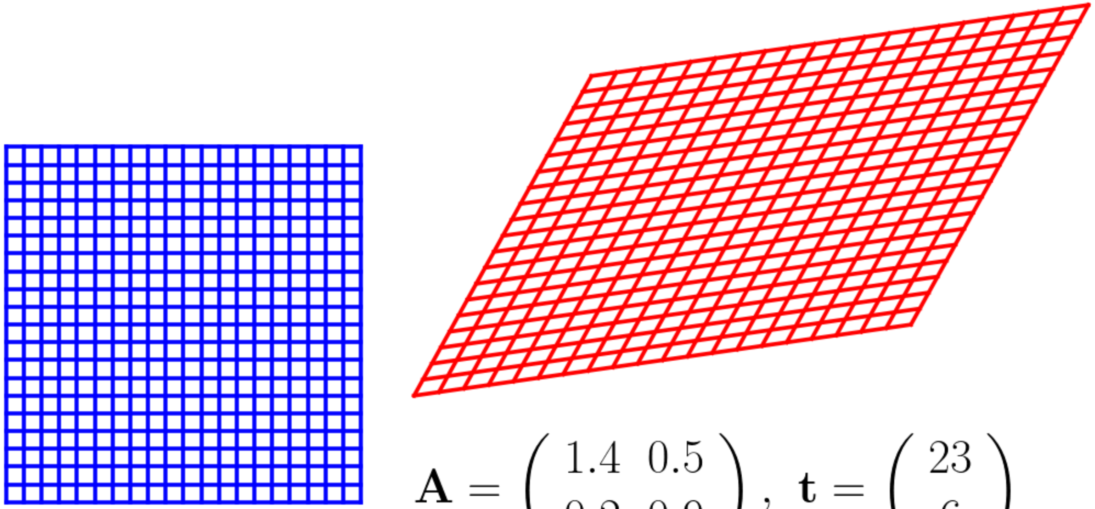
$$\mathbf{y}(\mathbf{x}, \mathbf{w}) = \mathbf{A}\mathbf{x} + \mathbf{t}$$



$$\mathbf{A} = \begin{pmatrix} 1.0 & 0.0 \\ 0.0 & 1.0 \end{pmatrix}, \quad \mathbf{t} = \begin{pmatrix} 23 \\ 6 \end{pmatrix}$$

Affine transformation

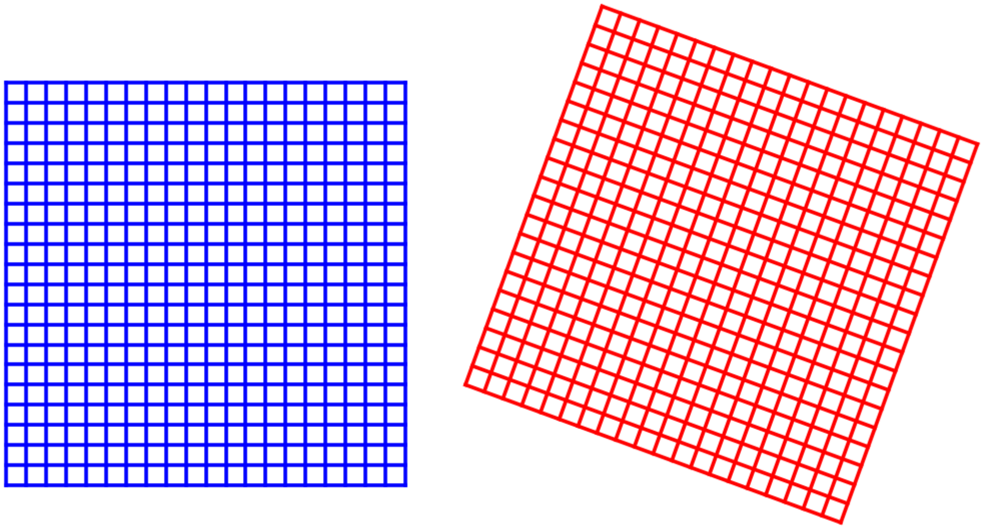
$$\mathbf{y}(\mathbf{x}, \mathbf{w}) = \mathbf{A}\mathbf{x} + \mathbf{t}$$



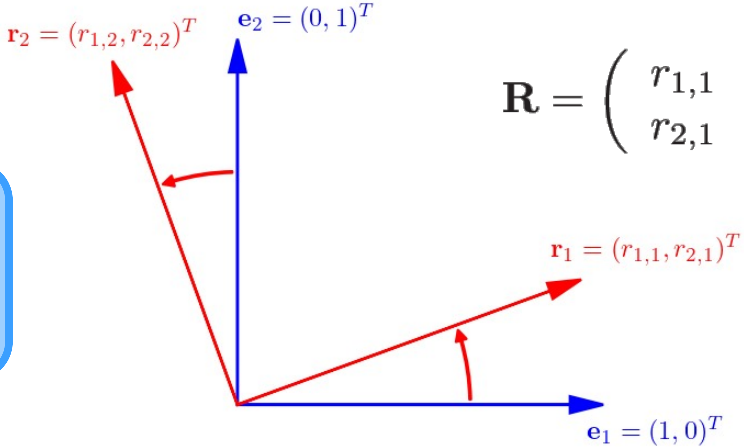
$$\mathbf{A} = \begin{pmatrix} 1.4 & 0.5 \\ 0.2 & 0.9 \end{pmatrix}, \quad \mathbf{t} = \begin{pmatrix} 23 \\ 6 \end{pmatrix}$$

Rigid transformation

$$\mathbf{y}(\mathbf{x}, \mathbf{w}) = \mathbf{R}\mathbf{x} + \mathbf{t}, \qquad \mathbf{R}^{\mathrm{T}}\mathbf{R} = \mathbf{I} \text{ and } \det(\mathbf{R}) = 1$$



Rigid transformation



$$\mathbf{R} = \begin{pmatrix} r_{1,1} & r_{1,2} \\ r_{2,1} & r_{2,2} \end{pmatrix}$$

Task: why do $\mathbf{R}^T\mathbf{R} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

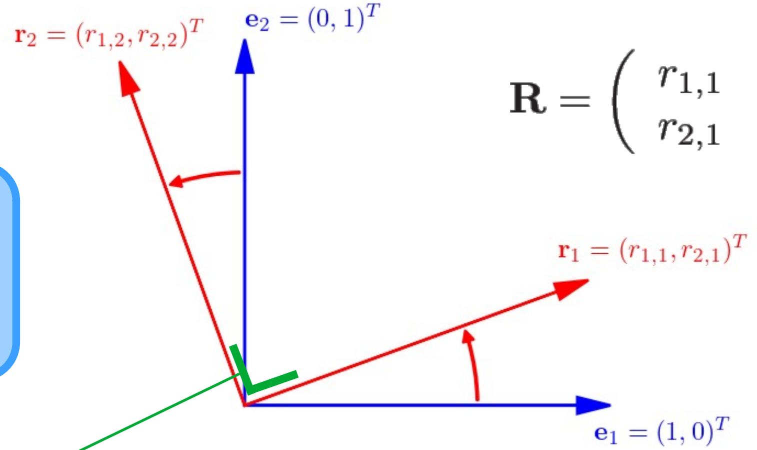
and $\det(\mathbf{R}) = 1$ impose a rotation?

Rigid transformation

$$\|\mathbf{r}_1\| = \sqrt{\mathbf{r}_1^T \mathbf{r}_1} = 1$$

Task: why do $\mathbf{R}^T\mathbf{R} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

and $\det(\mathbf{R}) = 1$ impose a rotation?



$$\mathbf{R} = \begin{pmatrix} r_{1,1} & r_{1,2} \\ r_{2,1} & r_{2,2} \end{pmatrix}$$

$$\mathbf{r}_1^T \mathbf{r}_2 = 0$$

$$\|\mathbf{r}_2\| = \sqrt{\mathbf{r}_2^T \mathbf{r}_2} = 1$$

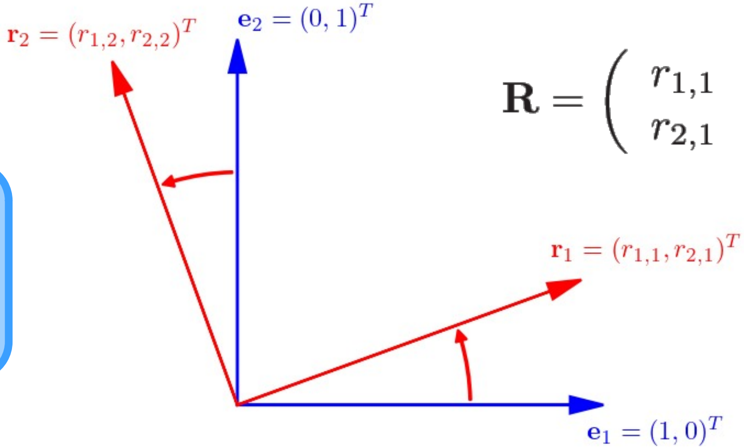
Rigid transformation

Task: why do $\mathbf{R}^T\mathbf{R} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

and $\det(\mathbf{R}) = 1$ impose a rotation?

?

$$\mathbf{R} = \begin{pmatrix} r_{1,1} & r_{1,2} \\ r_{2,1} & r_{2,2} \end{pmatrix}$$



Rigid transformation

Task: why do $\mathbf{R}^T\mathbf{R} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

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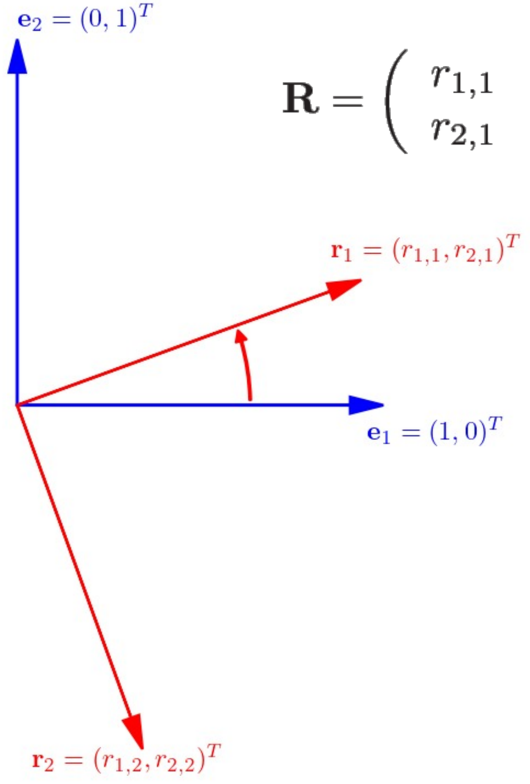
?

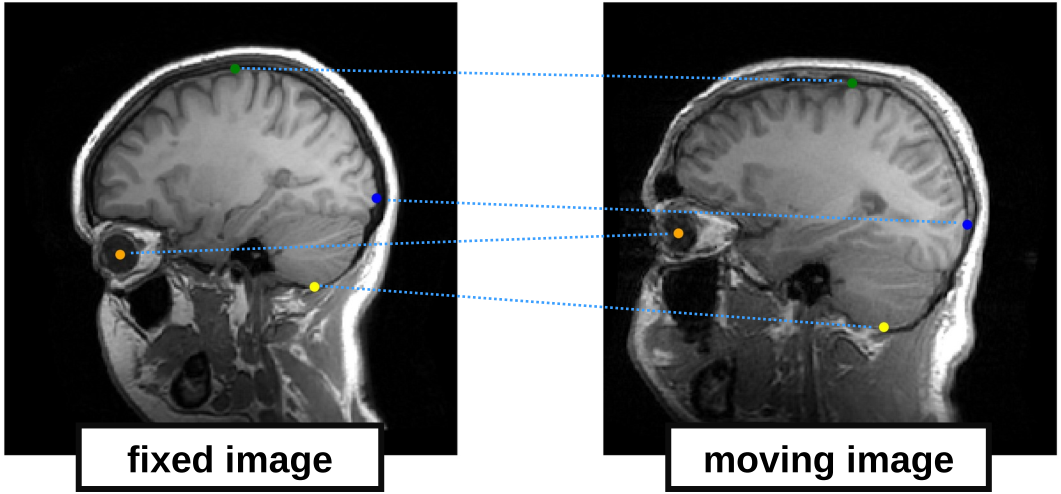
$$\mathbf{R} = \begin{pmatrix} r_{1,1} & r_{1,2} \\ r_{2,1} & r_{2,2} \end{pmatrix}$$



Landmark-based registration

- ✔ Manually annotate N corresponding points in two images:

$\{\mathbf{x}_n\}_{n=1}^{N}$



$\{\mathbf{y}_n\}_{n=1}^{N}$

- ✔ Register the images by minimizing the distance between matching point pairs:

$$E(\mathbf{w}) = \sum_{n=1}^{N} \|\mathbf{y}_n - \mathbf{y}(\mathbf{x}_n, \mathbf{w})\|^2$$

Landmark-based registration

Applied to affine registration: $E(\mathbf{w}) = \sum_{n=1}^{N} \|\mathbf{y}_n - \mathbf{A}\mathbf{x}_n - \mathbf{t}\|^2$

Task 1: if $\mathbf{A} = \mathbf{I}$, what is $\mathbf{t}$?

Hint: remember that $\|\mathbf{a} - \mathbf{b}\|^2 = \sum_{d=1}^{D}(a_d - b_d)^2$

Task 2: in the general case, what are $\mathbf{A}$ and $\mathbf{t}$?

Landmark-based registration

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$$\begin{pmatrix} t_d \\ a_{d,1} \\ \vdots \\ a_{d,D} \end{pmatrix} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}} \begin{pmatrix} y_{1,d} \\ \vdots \\ y_{N,d} \end{pmatrix}$$

where $\mathbf{X} = \begin{pmatrix} 1 & x_{1,1} & \cdots & x_{1,D} \\ 1 & x_{2,1} & \cdots & x_{2,D} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{N,1} & \cdots & x_{N,D} \end{pmatrix}$

Task 1: if $\mathbf{A} = \mathbf{I}$, what is $\mathbf{t}$?

Hint: remember that $\|\mathbf{a} - \mathbf{b}\|^2 = \sum_{d=1}^{D} (a_d - b_d)^2$

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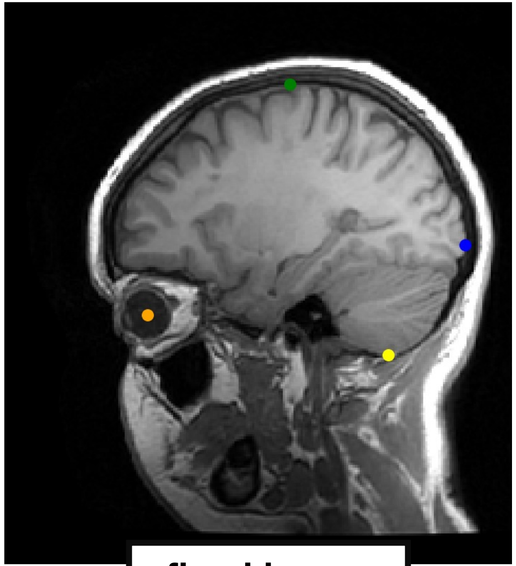
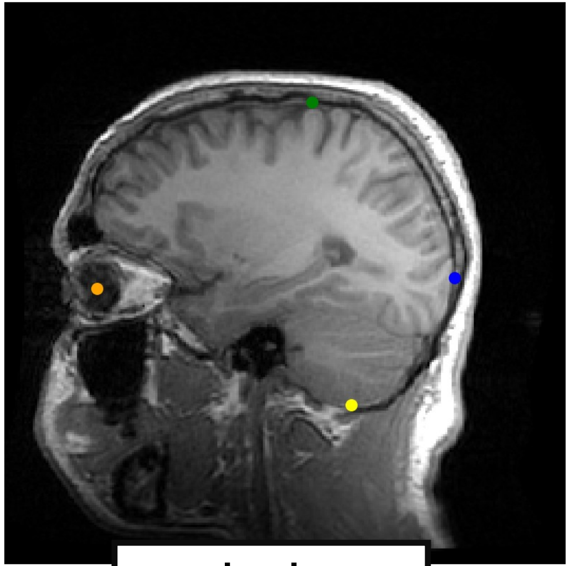
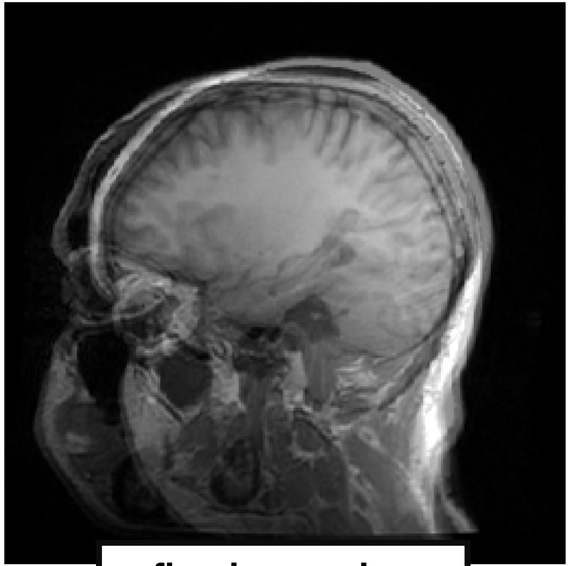
Landmark-based registration



fixed image



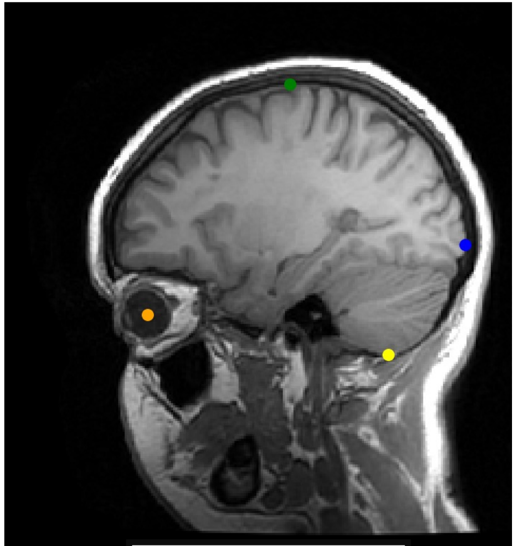
moving image



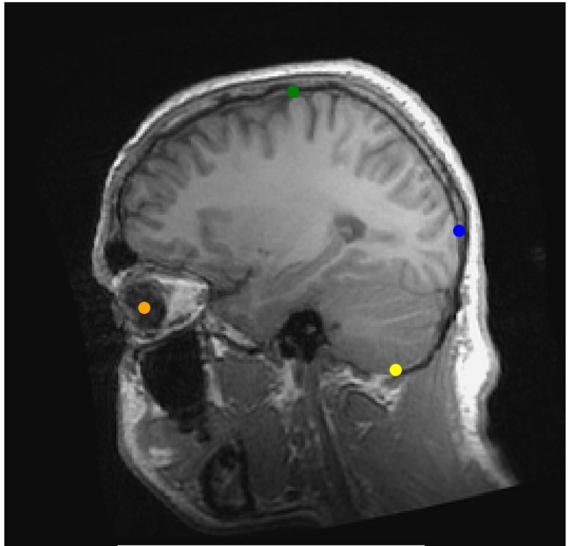
fixed + moving

Before registration

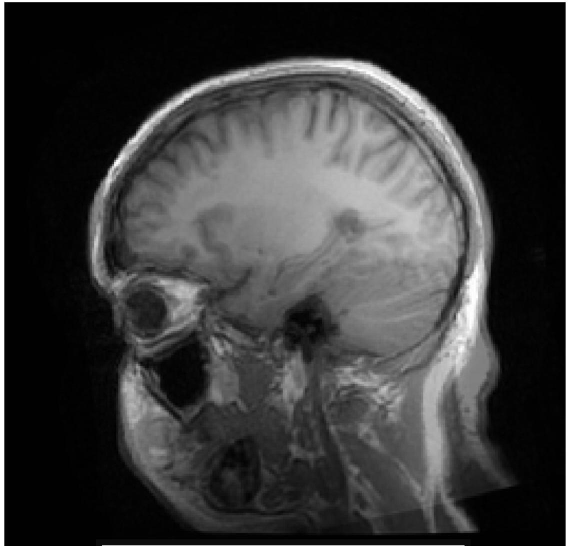
Landmark-based registration



fixed image



moving image

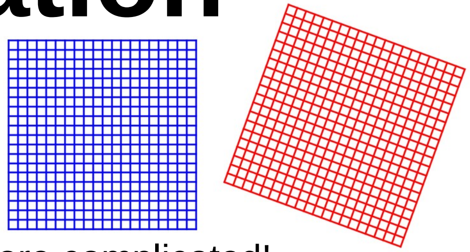


fixed + moving

After registration

Aalto-yliopisto
Aalto-universitetet
Aalto University

Landmark-based registration



Applied to *rigid* registration: $E(\mathbf{w}) = \sum_{n=1}^{N} \|\mathbf{y}_n - \mathbf{R}\mathbf{x}_n - \mathbf{t}\|^2$

- ✔ Constraints $\mathbf{R}^{\mathrm{T}}\mathbf{R} = \mathbf{I}$ and $\det(\mathbf{R}) = 1$ make the math much more complicated!
- ✔ Solution:

$$\mathbf{R} = \mathbf{V}\mathbf{U}^{\mathrm{T}}, \quad \sum_{n=1}^{N} \tilde{\mathbf{x}}_n \tilde{\mathbf{y}}_n^{\mathrm{T}} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{\mathrm{T}}, \quad \mathbf{U}^{\mathrm{T}}\mathbf{U} = \mathbf{I}, \quad \mathbf{V}^{\mathrm{T}}\mathbf{V} = \mathbf{I}$$

$$\mathbf{t} = \bar{\mathbf{y}} - \mathbf{R}\bar{\mathbf{x}},$$

where $\tilde{\mathbf{x}}_n = \mathbf{x}_n - \bar{\mathbf{x}}$ and $\tilde{\mathbf{y}}_n = \mathbf{y}_n - \bar{\mathbf{y}}$

with $\bar{\mathbf{x}} = \frac{1}{N} \sum_{n=1}^{N} \mathbf{x}_n$ and $\bar{\mathbf{y}} = \frac{1}{N} \sum_{n=1}^{N} \mathbf{y}_n$

(“flip” a column of $\mathbf{R}$ if $\det(\mathbf{R}) = -1$)