Outline

- Image registration and its purpose (examples)
  - Registration methods
  - Classes of transformations
  - Landmark-based registration
    - Rigid registration
    - Procrustes alignment
  - Assignment 1
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Image registration

Determine a geometrical transformation that aligns points in an image with corresponding points in other image(s)
Image registration

Determine a geometrical transformation that aligns points in an image with corresponding points in other image(s)
Purpose of image registration

*Adds value* to medical images by enabling:

- monitoring of change in the individual
- fusion of information from different sources in a clinically meaningful way
- comparison of one subject with others
- comparison of groups with others
Example: PET/MR

Before...
Example: PET/MR

...after
Example: CT/MR

Before...
Example: CT/MR

...after
Example: time series

Patient with Multiple Sclerosis

baseline
Example: time series

Patient with Multiple Sclerosis

after 2 months
Example: time series

Patient with Multiple Sclerosis

after 4 months
Example: time series

Patient with Multiple Sclerosis

after 6 months
Example: time series

Patient with Multiple Sclerosis

after 8 months
Example: time series

Patient with Multiple Sclerosis

after 10 months
Example: time series

Patient with Multiple Sclerosis

after 12 months
Spatial mappings (linear)

- **Translation**: $y(x; t) = x + t$
- **Rigid (translation + rotation)**: $y(x; R, t) = Rx + t$
  \[ R^T R = I, \quad \det(R) = 1 \]
- **Similarity transformation**: $y(x; s, R, t) = sRx + t$
  \[ s > 0 \]
- **Affine transformation**: $y(x; A, t) = Ax + t$
Where to use what?

Rigid transform:
• global patient repositioning (intra-subject)

Similarity transform:
• shape analysis

Affine transform:
• first step in non-linear registration
Spatial mappings (non-linear)

Models:
- Control points (e.g., interpolating thin plate spline)
- Basis functions (e.g., sines/cosines, B-spline basis functions)
- ...
Where to use what?

Non-rigid transformations:
- Tissue motion (cardiac cycle/respiratory motion)
- Deformation compensation (intra-operative, soft tissue)
- Longitudinal tissue changes (e.g., tumor growth)
- Inter-subject registration
Spatial mappings: parameters

Similarity transformation:
- $s, R, t$
- 4 degrees of freedom (dof) in 2D; 7 dof in 3D

Affine transformation:
- $A, t$
- 6 dof in 2D; 12 dof in 3D

Non-linear:
- Control point coordinates; basis function coefficients; ...
- 20 – 1,000,000 dof
Landmark based registration

- Geometrical transformation $y(x; w) : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ or $\mathbb{R}^3 \rightarrow \mathbb{R}^3$
- Similarity measure $\mathcal{D}(w)$
- Regularization $\mathcal{S}(w)$
- Optimization algorithm $\mathcal{J}(w) = \mathcal{D}(w) + \alpha \mathcal{S}(w)$
Landmark based registration

- Geometrical transformation \( y(x; w) : \mathbb{R}^2 \rightarrow \mathbb{R}^2 \) or \( \mathbb{R}^3 \rightarrow \mathbb{R}^3 \)
- Similarity measure \( D(w) \)
- Regularization \( S(w) \)
- Optimization algorithm \( J(w) = D(w) + \alpha S(w) \)

Match two corresponding point sets defined in two images: \( x_i, y_i \in \mathbb{R}^2 \) or \( \mathbb{R}^3 \)

\[
D(w) = \sum_{i=1}^{N} \| y(x_i; w) - y_i \|^2
\]
Types of landmarks

Anatomical landmark:
  • assigned by an expert; anatomically meaningful

Mathematical landmark:
  • computed based on mathematical/geometrical principles (e.g., max. curvature)

Pseudo landmark:
  • computed based on anatomical or mathematical landmarks (e.g., curve length)
Affine landmark based registration

- Affine transformation \( y(x; A, t) = Ax + t \)
- No regularization

Minimize

\[
\sum_{i=1}^{N} \| y(x_i; A, t) - y_i \|^2 = \sum_{i=1}^{N} \| (Ax_i + t - y_i) \|^2 = \sum_{i=1}^{N} \sum_{j=1}^{P} (y_j^i - t_j - \sum_{k=1}^{P} a_{jk} x_k^i)^2
\]

Standard linear regression!

\[
\begin{pmatrix}
  t_j \\
  a_{j1} \\
  \vdots \\
  a_{jP}
\end{pmatrix} = (X^T X)^{-1} X^T \begin{pmatrix}
  y_1^j \\
  \vdots \\
  y_N^j
\end{pmatrix}, \quad X = \begin{pmatrix}
  1 & x_1^1 & x_2^1 & \cdots & x_P^1 \\
  1 & x_1^2 & x_2^2 & \cdots & x_P^2 \\
  \vdots & \vdots & \vdots & \ddots & \vdots \\
  1 & x_1^N & x_2^N & \cdots & x_P^N
\end{pmatrix}
\]
Rigid landmark based registration

• Rigid transformation $y(x; R, t) = Rx + t$

• Rotation constraints $R^T R = I$, $\det(R) = 1$ make life much more difficult!

$$R = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} \quad (2D)$$

$$R = \begin{pmatrix} \cos \theta_3 & -\sin \theta_3 & 0 \\ \sin \theta_3 & \cos \theta_3 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \cos \theta_2 & 0 & -\sin \theta_2 \\ 0 & 1 & 0 \\ \sin \theta_2 & 0 & \cos \theta_2 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos \theta_1 & -\sin \theta_1 \\ 0 & \sin \theta_1 & \cos \theta_1 \end{pmatrix} \quad (3D)$$
▶ A geometrical transformation:

\[ y = y(x; w) : \mathbb{R}^d \rightarrow \mathbb{R}^d \]

where \( d = 2 \) or \( d = 3 \) and \( w \) is a parameter.

▶ A similarity measure \( D(w) \) and a regularizing term: \( S(w) \).

▶ Define the “energy”:

\[ E(w) := \lambda S(w) + D(w), \]

where \( \lambda \) is a nonnegative parameter (a weight).

▶ Solve the minimization problem:

\[ w_* = \arg\min_w E(w). \]

▶ The registration map is: \( y = y(x; w_*) \)
Image registration building blocks

- A geometrical transformation:
  \[ y = y(x; w) : \mathbb{R}^d \rightarrow \mathbb{R}^d \]
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A geometrical transformation:

\[ y = y(x; w) : \mathbb{R}^d \rightarrow \mathbb{R}^d \]

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Rigid Registration (Euclidean Transformations)

Given corresponding landmarks $x_i$ and $y_i$, $i = 1, \ldots, N$.

Find rotation $R_*$ and translation $t_*$ which solves

$$\min \sum_{i=1}^{N} \|y_i - t - Rx_i\|^2.$$ 

The algorithm: Set $\bar{x} = \sum_{i=1}^{N} x_i/N$ and $\bar{y} = \sum_{i=1}^{N} y_i/N$ (centroids), and define

$$\tilde{x}_i = x_i - \bar{x} \quad \text{and} \quad \tilde{y}_i = y_i - \bar{y}.$$ 

Let $H = \sum_{i=1}^{N} \tilde{y}_i \tilde{x}_i^T$ and use SVD to get $H = UDV^T$. Then

$$R_* = U \text{diag}(1, 1, \text{det}(UV^T)) V^T,$$

$$t_* = \bar{y} - R_* \bar{x}.$$ 

In 2D use $\text{diag}(1, \text{det}(UV^T))$. 
Rigid Registration (Euclidean Transformations)

Given corresponding landmarks $x_i$ and $y_i$, $i = 1, \ldots, N$.
Find rotation $R_*$ and translation $t_*$ which solves

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$$
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$$

$$
t_* = \bar{y} - R_* \bar{x}.
$$

In 2D use $\text{diag}(1, \det(UV^T))$. 

Given corresponding landmarks \( x_i \) and \( y_i \), \( i = 1, \ldots, N \).
Find rotation \( R_\star \) and translation \( t_\star \) which solves
\[
\min \sum_{i=1}^{N} \|y_i - t - Rx_i\|^2.
\]

**The algorithm:** Set \( \bar{x} = \sum_{i=1}^{N} x_i / N \) and \( \bar{y} = \sum_{i=1}^{N} y_i / N \) (centroids), and define
\[
\tilde{x}_i = x_i - \bar{x} \quad \text{and} \quad \tilde{y}_i = y_i - \bar{y}.
\]
Let \( H = \sum_{i=1}^{N} \tilde{y}_i \tilde{x}_i^T \) and use SVD to get \( H = U D V^T \). Then
\[
R_\star = U \diag(1, 1, \det(UV^T)) V^T,
\]
and
\[
t_\star = \bar{y} - R_\star \bar{x}.
\]
In 2D use \( \diag(1, \det(UV^T)) \).
Rigid Registration (Euclidean Transformations)

Given corresponding landmarks $x_i$ and $y_i$, $i = 1, \ldots, N$.
Find rotation $R_*$ and translation $t_*$ which solves

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The algorithm: Set $\bar{x} = \sum_{i=1}^{N} x_i / N$ and $\bar{y} = \sum_{i=1}^{N} y_i / N$ (centroids), and define

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In 2D use $\text{diag}(1, \det(UV^T))$. 
A Simple Registration Problem. Image Transformation by Pullback

- Determine the a map $\Phi$ which aligns the hands.

- Transform $\mathcal{T}$ into the reference frame of $\mathcal{R}$ using the pullback transformation:

  If $y = \Phi(x)$ then

  $$\Phi^*\mathcal{T}(x) = \mathcal{T}(\Phi(x))$$

  is the pullback of $\mathcal{T}$ by $\Phi$. 
Rigid Registration

Reference image ($\mathcal{R}$)

Template image ($\mathcal{T}$)

Pullback of $\mathcal{T}$ to $\mathcal{R}$

Landmarks mapped back

Transformed point set. Angle = -25.7469°, Norm of translation vector = 293.1459

N. Chr. Overgaard Lecture 2 2018-11-09 7 / 14
Registration using Similarity Transforms (Procrustes)

Find the rotation \( R_* \), translation \( t_* \) and scale \( s_* \) which solves

\[
\min \sum_{i=1}^{N} \| y_i - t - sR x_i \|^2.
\]

The algorithm: Set \( \bar{x} = \sum_{i=1}^{N} x_i / N \) and \( \bar{y} = \sum_{i=1}^{N} y_i / N \), and define

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\tilde{x}_i = x_i - \bar{x} \quad \text{and} \quad \tilde{y}_i = y_i - \bar{y}.
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\[
R_* = U \text{diag}(1, 1, \det(UV^T))V^T,
\]

\[
s_* = \frac{\sum_{i=1}^{N} \tilde{y}_i^T R_* \tilde{x}_i}{\sum_{i=1}^{N} \| \tilde{x}_i \|^2},
\]

\[
t_* = \bar{y} - s_* R_* \bar{x}.
\]
Registration using Similarity Transforms (Procrustes)

Find the rotation $R_*$, translation $t_*$ and scale $s_*$ which solves

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Registration using Similarity Transforms (Procrustes)

Find the rotation $R_*$, translation $t_*$ and scale $s_*$ which solves

$$
\min_N \sum_{i=1}^N \|y_i - t - sRx_i\|^2.
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The algorithm: Set \( \bar{x} = \sum_{i=1}^N x_i / N \) and \( \bar{y} = \sum_{i=1}^N y_i / N \), and define

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\]

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s_* = \frac{\sum_{i=1}^N \tilde{y}_i^T R_* \tilde{x}_i}{\sum_{i=1}^N \|\tilde{x}_i\|^2},
\]

\[
t_* = \bar{y} - s_* R_* \bar{x}.
\]
Example of Similarity Registration

Reference image (\(R\))

Template image (\(T\))

Pullback of \(T\) to \(R\) (Scale = 0.96)

Landmarks mapped back
Overfitting the model?

Reference image ($\mathcal{R}$)

Template image ($\mathcal{T}$)

Pullback of $\mathcal{T}$ to $\mathcal{R}$
(Notice the scale: 1.12)

Landmarks mapped back.
Assignment 1

- Topic: Landmark-based registration of histopatological images using SIFT and RANSAC
  - Data and instructions available from Friday 9 November
  - Deadline: 23:59 Sunday 25 November
  - Submit the report as pdf
  - All m-files (well-commented and ready to run) as zip-files
  - Give the submitted report the name: assignment-1-yourname.pdf
  - Send to fman301th@man.lth.se.
  - Supervision: Monday 12 Nov 10–12, Wednesday 14 Nov 8–10, Monday 19 Nov 10–12 and Wednesday 21 Nov 8–10 in MH:231 (Ask your assignment-related questions to PhD-student David Gillsjö)
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The Histopathological Images (Prostate specimen)

- Tissue section stained with Hematoxiline-Eosine
- Adjacent tissue section stained with p63AMACR
Finding Keypoints using SIFT

SIFT keypoints and descriptors for H&E.

SIFT keypoints and descriptors for p63AMACR.

Here 50 keypoints were selected at random among 4824 and 6906, respectively.
Tak for god ro og orden!
Some of the slides used were borrowed from:

Koen Van Leemput
DTU Compute
Danmarks Tekniske Universitet

He and Professor Rasmus Larsen have generously shared their lecture notes and slides with us.