# 3D Image Registration summary 

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## 3D Image Registration

- 3D solid motion models
- Image registration
- 3D Point cloud registration


## 2D motion models

- 2D solid motion model:
- Motion from 2D point $[x, y]^{T}$ to point $\left[x^{\prime}, y^{\prime}\right]^{T}$ :

$$
\left[\begin{array}{l}
x^{\prime} \\
y^{\prime}
\end{array}\right]=\left[\begin{array}{ll}
r_{11} & r_{12} \\
r_{21} & r_{22}
\end{array}\right]\left[\begin{array}{l}
x \\
y
\end{array}\right]+\left[\begin{array}{l}
T_{x} \\
T_{y}
\end{array}\right] .
$$

- From the 6 relevant parameters, only 3 are independent:
- 1 rotation parameter (rotation angle) and the 2 translation vector components).


## 2D motion models

Geometric image transforms

- 2D Image translation:

$$
b[i][j]=a[i+k][j+1] .
$$

- 2D Image rotation: If the image point $a(x, y)$ is rotated by $\theta$ degrees, its new coordinates $\left(x^{\prime}, y^{\prime}\right)$ are given by:

$$
\left[\begin{array}{l}
x^{\prime} \\
y^{\prime}
\end{array}\right]=\left[\begin{array}{cc}
\cos \theta & -\sin \theta \\
\sin \theta & \cos \theta
\end{array}\right]\left[\begin{array}{l}
x \\
y
\end{array}\right] .
$$

## 2D motion models



## 3D motion models

- 3D solid object motion can be described by the affine transformation:

$$
\mathbf{X}^{\prime}=\mathbf{R X}+\mathbf{T},
$$

where $\mathbf{T}$ is a $3 \times 1$ translation vector:

$$
\mathbf{T}=\left[\begin{array}{l}
T_{X} \\
T_{Y} \\
T_{Z}
\end{array}\right]
$$

and $\mathbf{R}$ is a $3 \times 3$ rotation matrix (having various forms).

## 3D motion models

- In Cartesian coordinates, $\mathbf{R}$ can be described:
- either by the Euler rotation angles about the three coordinate axes $X, Y, Z$.
- or by a rotation axis and a rotation angle about this axis.
- The matrices describing the clockwise rotation around each axis in the three-dimensional space, are given by:

$$
\mathbf{R}=\mathbf{R}_{Z} \mathbf{R}_{Y} \mathbf{R}_{X}
$$

- Their order does matter.
- $\mathbf{R}$ is orthonormal, satisfying $\mathbf{R}^{T}=\mathbf{R}^{-1}$ and $\operatorname{det}(\mathbf{R})= \pm 1$.


## 3D motion models



Euler rotation angles.

$$
\mathbf{R}_{X}=\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & \cos \theta & -\sin \theta \\
0 & \sin \theta & \cos \theta
\end{array}\right],
$$

$$
\mathbf{R}_{Y}=\left[\begin{array}{ccc}
\cos \psi & 0 & \sin \psi \\
0 & 1 & 0 \\
-\sin \psi & 0 & \cos \psi
\end{array}\right],
$$

$$
\mathbf{R}_{Z}=\left[\begin{array}{ccc}
\cos \varphi & -\sin \varphi & 0 \\
\sin \varphi & \cos \varphi & 0 \\
0 & 0 & 1
\end{array}\right] .
$$

## 3D motion models



Object rotation about a rotation axis.

## 3D motion models

-3D rotation can also be represented by quaternions that are extensions of complex numbers:

$$
\mathbf{q}=q_{0}+q_{1} \mathbf{i}+q_{2} \mathbf{j}+q_{3} \mathbf{k}
$$

$q_{0}, q_{1}, q_{2}, q_{3}$ are real numbers and:

$$
\mathbf{i}^{2}=\mathbf{j}^{2}=\mathbf{k}^{2}=\mathbf{i} \mathbf{j} \mathbf{k}=-1
$$

- Unit quaternion $\mathbf{q}_{R}=\left[\begin{array}{lll}q_{0} & q_{1} & q_{2}\end{array} q_{3}\right]^{T}$. It satisfies:

$$
q_{0}^{2}+q_{1}^{2}+q_{2}^{2}+q_{3}^{2}=1
$$

## 3D motion models

- 3D solid motion model:

$$
\left[\begin{array}{l}
X^{\prime} \\
Y^{\prime} \\
Z^{\prime}
\end{array}\right]=\left[\begin{array}{lll}
r_{11} & r_{12} & r_{13} \\
r_{21} & r_{22} & r_{23} \\
r_{31} & r_{32} & r_{33}
\end{array}\right]\left[\begin{array}{l}
X \\
Y \\
Z
\end{array}\right]+\left[\begin{array}{l}
T_{X} \\
T_{Y} \\
T_{Z}
\end{array}\right] .
$$

- From the 12 relevant parameters, only 6 are independent (3 rotation parameters and the 3 translation vector components).


## Image registration

- 2D/3D solid motion models
- Image registration
- 2D image registration
- 3D image registration
- Point cloud registration
- 2D point cloud registration
- 3D point cloud registration


## 2D Image registration

- 2D affine mapping transformation: it describes 2D rotation, translation and scaling.
- It can be used for 2D image registration and subtraction.

Subtractive radiography.


## 2D Image registration

- 2D affine transformation for image registration.
- Overlapping image regions are registered and mosaicking.


## 2D Image registration

- 2D image registration and mosaicking.



## Image registration

- 3D solid motion models
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- Point cloud registration
- 2D point cloud registration
- 3D point cloud registration


## 3D point cloud registration

- Registration of two 3D datasets is a common problem in 3D image analysis.
- Methods are distinguished by the type of geometric transforms they handle and whether the correspondence between matching points is known or not.
- The most used method is Iterative Closest Point (ICP).
- It handles rigid transformations consisting of rotations and translations without a-priori knowledge of the correspondence between points.
- The algorithm handles various types of data, including point sets, line segment sets, triangle sets and implicit/parametric surfaces.


## 3D point cloud registration


a) Model 3D tooth; b) Slice of model 3D tooth; c) Slice of data volume (3D tooth model rotated and translated along $x$-axis and translated along $y$ axis); d) Overlaid model (red channel) and registered (green channel) 3D tooth.

## 3D point cloud registration

The simplest case of the ICP algorithm is registration of two sets of geometrical data represented as point sets.

- Let $N_{p}, N_{x}$ be the number of points in sets $\mathcal{P}, \mathcal{X}$ respectively:

$$
\begin{array}{ll}
\mathcal{P}=\left\{\mathbf{p}_{i}\right\}, & i=1, \ldots, N_{p}, \\
\mathcal{X}=\left\{\mathbf{x}_{i}\right\}, & i=1, \ldots, N_{x},
\end{array}
$$

- $\mathbf{p}_{i}, \mathbf{x}_{i}$ the 3D vectors (voxel coordinates):

$$
\mathbf{x}_{i}=\left[X_{i} Y_{i} Z_{i}\right]^{T} .
$$

## ICP algorithm

ICP algorithm is an iterative algorithm that evaluates the correspondence between two 3D point sets.

- It estimates the optimum registration vector (the set of translation and rotation parameters that lead to the optimum registration)
- It applies the derived transformation to one of the sets.

The process is repeated until a certain dissimilarity measure (e.g., the mean square error) becomes smaller than a certain value.

## SVD 3D Point Cloud Registration

- SVD-based methods demonstrate highest accuracy and stability when compared to quaternion-based methods [LIN2017].
- They are still inferior to ICP [BEL2015].


## SVD 3D Point Cloud Registration

- First, it is assumed that the centroid of $\mathcal{P}$ is translated to the centroid of $\mathcal{X}$. Thus, restating the problem without translation, the points of the two sets can be rewritten as:

$$
\begin{gathered}
\mathcal{P}_{c}=\left\{\mathbf{p}_{i}-\boldsymbol{\mu}_{p}, i=1, \ldots, N_{p}\right\}, \\
X_{c}=\left\{\mathbf{x}_{i}-\boldsymbol{\mu}_{x}, i=1, \ldots, N_{x}\right\}, \\
\boldsymbol{\mu}_{p}=\frac{1}{N_{p}} \sum_{i=1}^{N_{p}} \mathbf{p}_{i}, \quad \boldsymbol{\mu}_{x}=\frac{1}{N_{x}} \sum_{i=1}^{N_{x}} \mathbf{x}_{i} .
\end{gathered}
$$

- Using the points of the two sets $\mathcal{P}_{c}, X_{c}$ the matrices $\mathbf{P}_{c} \in$ $\mathcal{R}^{N_{p} \times 3}, \mathbf{X}_{c} \in \mathcal{R}^{N_{x} \times 3}$ are created. From now on we assume $N_{p}=$ $N_{x}=N$.


## SVD 3D Point Cloud Registration

- Optimal rotation $\mathbf{R}$ implies the minimization of the transformation error:

$$
\mathbf{R}=\operatorname{argmin}_{\mathbf{R}}\left\|\mathbf{X}_{c}-\mathbf{P}_{c} \mathbf{R}\right\|_{F}^{2} .
$$

- This is an orthogonal Procrustes problem.
- Matrix approximation problem.
- Frobenius norm $\|\cdot\|_{F}$ is defined as:

$$
\|A\|_{F}=\sqrt{\operatorname{tr}\left(A^{T} A\right)}=\sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} a_{i j}^{2}}
$$

## Q \& A

Thank you very much for your attention!
More material in
http://icarus.csd.auth.gr/cvml-web-lecture-series/

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