

Geometry in Computer Vision

Spring 2010

Lecture 7A

Representations of 3D rotations

7 May 2010

Geometry in Computer Vision
Klas Nordberg

1

Orthogonal transformations

- From linear algebra we know that for a vector space V there is a special set of transformations \mathbf{A} known as *orthogonal transformations* (or *self-adjoint* transf.)

$$(\mathbf{A} \mathbf{x}) \cdot \mathbf{y} = \mathbf{x} \cdot (\mathbf{A} \mathbf{y}) \quad \text{for all } \mathbf{x}, \mathbf{y} \in V$$

$$\mathbf{A}^T \mathbf{A} = \mathbf{A} \mathbf{A}^T = \mathbf{I}$$

These two definitions are equivalent (*why?*)

7 May 2010

Geometry in Computer Vision
Klas Nordberg

2

Orthogonal transformations

- For $V=\mathbb{R}^3$, the set of orthogonal transformations is denoted $O(3)$
- $O(3)$ are represented by 3×3 matrices that satisfy $\mathbf{A}^T \mathbf{A} = \mathbf{I}$ (or $\mathbf{A}^T = \mathbf{A}^{-1}$)
- From $\mathbf{A}^T \mathbf{A} = \mathbf{I}$ follows that $\det \mathbf{A} = \pm 1$ (*why?*)
- $O(3)$ consists of two *disconnected parts* in the space of 3×3 matrices:
 - one with $\det \mathbf{A} = 1$
 - one with $\det \mathbf{A} = -1$
- $O(3)$ forms a *group* under matrix multiplication

7 May 2010

Geometry in Computer Vision
Klas Nordberg

3

3D Rotations

- The set of $O(3)$ with $\det \mathbf{A} = 1$ are *3D rotations*
- Also known as the *special orthogonal transformations*
- Denoted $SO(3)$
- Forms a group under matrix multiplication
- The set of $O(3)$ with $\det \mathbf{A} = -1$ do not form a group (*why?*)
- This set includes mirroring operations

7 May 2010

Geometry in Computer Vision
Klas Nordberg

4

Representations

- In many applications we want to determine a rotation:
 - External camera parameters include a rotation
 - \mathbf{E} is determined by a rotation and a translation
 - Find the rigid transformation between 2 point sets; it includes a rotation
 - Bundle adjustment ...
- To solve such problems, we often need to parameterize the set of rotations: $SO(3)$

3D Rotations

- A 3D rotation \mathbf{R} is characterized by a
 - normalized vector \mathbf{n} (2 d.o.f.)
 - rotation angle α (1 d.o.f.)
 - α is well-defined, e.g., using the right-hand-rule
- \mathbf{R} rotates around the vector \mathbf{n} with the angle α
- Note: (\mathbf{n}, α) is equivalent to $(-\mathbf{n}, -\alpha)$
- In total: 3 degrees of freedom

Euler angles

- We can decompose any $\mathbf{R} \in SO(3)$ into a product of 3 rotations around *fixed axes*
- For example:
$$\mathbf{R} = \text{Rot}_z(\alpha_1) \text{Rot}_x(\alpha_2) \text{Rot}_z(\alpha_3)$$
- $(\alpha_1, \alpha_2, \alpha_3)$ are the *Euler angles* of \mathbf{R}

Euler angles

- $(\alpha_1, \alpha_2, \alpha_3)$ are unique (modulo $2\pi, \pi, 2\pi$)
- Non-trivial relation between $(\alpha_1, \alpha_2, \alpha_3)$ and (\mathbf{n}, α)
- Non-trivial to combine two rotations
- Non-trivial mapping $\mathbf{R} \rightarrow (\alpha_1, \alpha_2, \alpha_3)$
- Not very interesting for practical applications

Vector \mathbf{n} and angle α

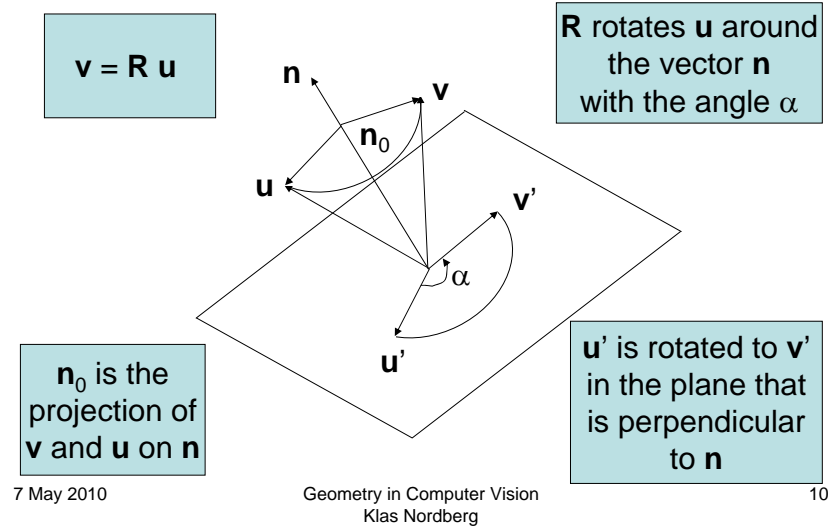
- (\mathbf{n}, α) is a convenient representation
 - With $|\mathbf{n}|=1$
 - Explicitly describes the rotation axis and angle
- But
 - Not unique unless we impose restrictions on (\mathbf{n}, α)
 - Not trivial to combine two rotations
- How do we map $\mathbf{R} \leftrightarrow (\mathbf{n}, \alpha)$?

7 May 2010

Geometry in Computer Vision
Klas Nordberg

9

The anatomy of a 3D rotation



The anatomy of a 3D rotation

- \mathbf{v} can be decomposed as $\mathbf{v} = \mathbf{n}_0 + \mathbf{v}'$
- where \mathbf{n}_0 is the projection of \mathbf{u} onto \mathbf{n}

$$\mathbf{n}_0 = \mathbf{n} \mathbf{n}^T \mathbf{u}$$

and \mathbf{v}' is the rotation of \mathbf{u}' in the plane perpendicular to \mathbf{n}

7 May 2010

Geometry in Computer Vision
Klas Nordberg

11

The anatomy of a 3D rotation

- Let (\mathbf{p}, \mathbf{q}) be an ON-basis for the plane that is perpendicular to \mathbf{n}
- The coordinates of \mathbf{u}' in this basis is $(\mathbf{p}^T \mathbf{u}', \mathbf{q}^T \mathbf{u}')$
- The coordinates of \mathbf{v}' in this basis is $(\mathbf{p}^T \mathbf{v}', \mathbf{q}^T \mathbf{v}')$

and

$$\begin{pmatrix} \mathbf{p}^T \mathbf{v}' \\ \mathbf{q}^T \mathbf{v}' \end{pmatrix} = \begin{pmatrix} \cos \alpha & -\sin \alpha \\ \sin \alpha & \cos \alpha \end{pmatrix} \begin{pmatrix} \mathbf{p}^T \mathbf{u}' \\ \mathbf{q}^T \mathbf{u}' \end{pmatrix}$$

7 May 2010

Geometry in Computer Vision
Klas Nordberg

12

The anatomy of a 3D rotation

- From this we get

$$\mathbf{v}' = (\mathbf{p} \ \mathbf{q}) \begin{pmatrix} \mathbf{p}^T \mathbf{v}' \\ \mathbf{q}^T \mathbf{v}' \end{pmatrix} = (\mathbf{p} \ \mathbf{q}) \begin{pmatrix} \cos \alpha & -\sin \alpha \\ \sin \alpha & \cos \alpha \end{pmatrix} \begin{pmatrix} \mathbf{p}^T \\ \mathbf{q}^T \end{pmatrix} \mathbf{u}$$

$$\mathbf{v}' = (\cos \alpha (\mathbf{p}\mathbf{p}^T + \mathbf{q}\mathbf{q}^T) + \sin \alpha [\mathbf{q}\mathbf{p}^T - \mathbf{p}\mathbf{q}^T]) \mathbf{u}$$

$$\mathbf{v} = (\mathbf{n}\mathbf{n}^T + \cos \alpha (\mathbf{I} - \mathbf{n}\mathbf{n}^T) + \sin \alpha [\mathbf{n}]_{\times}) \mathbf{u}$$

$$\mathbf{v} = (\mathbf{I} + (1 - \cos \alpha) [\mathbf{n}]_{\times}^2 + \sin \alpha [\mathbf{n}]_{\times}) \mathbf{u}$$

Rodrigues' formula

- This gives *Rodrigues' formula* for \mathbf{R} :

$$\mathbf{R} = \mathbf{I} + (1 - \cos \alpha) [\mathbf{n}]_{\times}^2 + \sin \alpha [\mathbf{n}]_{\times}$$

- This gives us a mapping $(\mathbf{n}, \alpha) \rightarrow \mathbf{R}$
- How do we map $\mathbf{R} \rightarrow (\mathbf{n}, \alpha)$?

Rodrigues' formula (II)

From this formula follows directly:

$$\text{tr } \mathbf{R} = \text{tr} (\mathbf{I} + (1 - \cos \alpha) [\mathbf{n}]_{\times}^2 + \sin \alpha [\mathbf{n}]_{\times})$$

$$\text{tr } \mathbf{R} = 3 + (1 - \cos \alpha) (-2) + \sin \alpha 0$$

and we get

$$\frac{\text{tr } \mathbf{R} - 1}{2} = \cos \alpha$$

Rodrigues' formula (II)

Rodrigues' formula also gives

$$\frac{\mathbf{R} - \mathbf{R}^T}{2} = \sin \alpha [\mathbf{n}]_{\times}$$

- From these last two relations we can solve for (\mathbf{n}, α) (**how?**)

Eigensystem of \mathbf{R}

- Clearly: $\mathbf{R} \mathbf{n} = \mathbf{n} \Rightarrow$
 \mathbf{n} is an eigenvector of \mathbf{R} with eigenvalue 1
- Maybe less clear:

$$\mathbf{R} (\mathbf{p} + i \mathbf{q}) = e^{i\alpha} (\mathbf{p} + i \mathbf{q})$$

$$\mathbf{R} (\mathbf{p} - i \mathbf{q}) = e^{-i\alpha} (\mathbf{p} - i \mathbf{q})$$

$$i^2 = -1$$

$(\mathbf{p} + i \mathbf{q})$ is an eigenvector of \mathbf{R} with eigenvalue $e^{i\alpha}$

$(\mathbf{p} - i \mathbf{q})$ is an eigenvector of \mathbf{R} with eigenvalue $e^{-i\alpha}$

(why?)

7 May 2010

Geometry in Computer Vision
Klas Nordberg

17

Eigensystem of \mathbf{R}

- The eigenvalues of \mathbf{R} are $(1, e^{i\alpha}, e^{-i\alpha})$
- They are the solutions to $\det(\mathbf{R} - \lambda \mathbf{I}) = 0$
- The corresponding *normalized* eigenvectors are

$$\left(\mathbf{n}, \frac{\mathbf{p} + i \mathbf{q}}{\sqrt{2}}, \frac{\mathbf{p} - i \mathbf{q}}{\sqrt{2}} \right)$$

\mathbf{p} and \mathbf{q} are not uniquely defined (why?)

- (\mathbf{n}, α) are given by an EVD of \mathbf{R}

7 May 2010

Geometry in Computer Vision
Klas Nordberg

18

Eigensystem of \mathbf{R}

- In summary we can write

$$\mathbf{R} = \left(\mathbf{n} \quad \frac{\mathbf{p} + i \mathbf{q}}{\sqrt{2}} \quad \frac{\mathbf{p} - i \mathbf{q}}{\sqrt{2}} \right) \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{i\alpha} & 0 \\ 0 & 0 & e^{-i\alpha} \end{pmatrix} \begin{pmatrix} \mathbf{n} & \frac{\mathbf{p} + i \mathbf{q}}{\sqrt{2}} & \frac{\mathbf{p} - i \mathbf{q}}{\sqrt{2}} \end{pmatrix}^*$$

Complex conjugation and transpose

- $\mathbf{R} = \mathbf{E} \mathbf{D} \mathbf{E}^*$
- \mathbf{E} is a unitary basis: $\mathbf{E}^* \mathbf{E} = \mathbf{I}$
- Can we connect this to Rodrigues' formula?

7 May 2010

Geometry in Computer Vision
Klas Nordberg

19

Matrix exponentials

- For a vector space V and a linear transformation $\mathbf{T}: V \rightarrow V$ we define the matrix exponential of \mathbf{T} as

$$e^{\mathbf{T}} = \sum_{k=0}^{\infty} \frac{1}{k!} \mathbf{T}^k = \mathbf{I} + \mathbf{T} + \frac{1}{2} \mathbf{T}^2 + \dots$$

- This series is absolute convergent for any \mathbf{T} , with $\mathbf{T}^0 = \mathbf{I}$
- $e^{\mathbf{T}}$ is linear transformation: $V \rightarrow V$

7 May 2010

Geometry in Computer Vision
Klas Nordberg

20

Matrix exponentials

General properties:

- $e^0 = \mathbf{I}$
- $e^{a\mathbf{T}} e^{b\mathbf{T}} = e^{(a+b)\mathbf{T}}$ (why?)
- $e^{\mathbf{T}^T} = (e^{\mathbf{T}})^T$ (why?)
- $e^{-\mathbf{T}} = (e^{\mathbf{T}})^{-1}$ (why?)
- $e^{\mathbf{E}\mathbf{D}\mathbf{E}^*} = \mathbf{E} e^{\mathbf{D}} \mathbf{E}^*$ for unitary \mathbf{E} ($\mathbf{E}^* \mathbf{E} = \mathbf{I}$) (why?)
- $e^{\mathbf{D}} = \text{diag}(e^{d_1}, e^{d_2}, \dots)$ for $\mathbf{D} = \text{diag}(d_1, d_2, \dots)$ (why?)

so(3)

- The set of skew-symmetric matrices is denoted so(3)
- $[\mathbf{m}]_{\times} \in \text{so}(3), \Rightarrow [\mathbf{m}]_{\times} = -[\mathbf{m}]_{\times}^T$
- $e^{[\mathbf{m}]_{\times}} = e^{-[\mathbf{m}]_{\times}^T} = (e^{-[\mathbf{m}]_{\times}})^T = ((e^{[\mathbf{m}]_{\times}})^{-1})^T$
 $\Rightarrow e^{[\mathbf{m}]_{\times}} \in \text{SO}(3)$
- The matrix exponential maps $\text{so}(3) \rightarrow \text{SO}(3)$

Eigensystem of $\alpha[\mathbf{n}]_{\times}$

- Clearly: $\alpha[\mathbf{n}]_{\times} \mathbf{n} = \mathbf{0} \Rightarrow$
 \mathbf{n} is an eigenvector of $\alpha[\mathbf{n}]_{\times}$ with eigenvalue 0

- Furthermore:

$$\alpha[\mathbf{n}]_{\times} (\mathbf{p} + i \mathbf{q}) = i\alpha (\mathbf{p} + i \mathbf{q})$$

$$\alpha[\mathbf{n}]_{\times} (\mathbf{p} - i \mathbf{q}) = -i\alpha (\mathbf{p} - i \mathbf{q})$$

$(\mathbf{p} + i \mathbf{q})$ is an eigenvector of $\alpha[\mathbf{n}]_{\times}$ with eigenvalue $i\alpha$

$(\mathbf{p} - i \mathbf{q})$ is an eigenvector of $\alpha[\mathbf{n}]_{\times}$ with eigenvalue $-i\alpha$

(why?)

$$i^2 = -1$$

Eigensystem of $\alpha[\mathbf{n}]_{\times}$

- The eigenvalues of $\alpha[\mathbf{n}]_{\times}$ are $(0, i\alpha, -i\alpha)$
- The corresponding *normalized* eigenvectors are

$$\left(\mathbf{n}, \frac{\mathbf{p} + i \mathbf{q}}{\sqrt{2}}, \frac{\mathbf{p} - i \mathbf{q}}{\sqrt{2}} \right)$$

- Same eigenvectors as \mathbf{R} !
- $\alpha[\mathbf{n}]_{\times} = \mathbf{E} \mathbf{D}' \mathbf{E}^*$ with $\mathbf{D}' = \text{diag}(0, i\alpha, -i\alpha)$
- Note: $\mathbf{D} = e^{\mathbf{D}'}$

so(3) → SO(3)

For $\mathbf{m} = \alpha\mathbf{n}$ we get:

$$e^{\alpha[\mathbf{n}]_{\times}} = e^{\mathbf{E}\mathbf{D}'\mathbf{E}^*} = \mathbf{E} e^{\mathbf{D}'} \mathbf{E}^* = \mathbf{E} \mathbf{D} \mathbf{E}^* = \mathbf{R}$$

so(3) → SO(3)

Summary:

- The matrix exponential maps $\alpha[\mathbf{n}]_{\times}$ to \mathbf{R}
- We can represent any \mathbf{R} as the skew-symmetric matrix $\alpha[\mathbf{n}]_{\times}$ which has 3 parameters
- We can represent any \mathbf{R} as the 3-dim vector $\mathbf{m}=\alpha\mathbf{n}$
- If we restrict \mathbf{m} to $|\mathbf{m}| < \pi$, this representation is, in principle, one-to-one

Quaternions

- Quaternions are an extension of complex numbers, with 4 components instead of 2
- Quaternions form an associative division algebra
 - They can be added, subtracted, multiplied, and divided
 - Are non-commutative
- Can be represented as a 4-dim vector
- Alternatively as a scalar + a vector

Quaternion algebra

- Using the scalar+vector notation:

$$\mathbf{q}_1 = (s_1, \mathbf{v}_1), \quad \mathbf{q}_2 = (s_2, \mathbf{v}_2)$$

$$\mathbf{q}_1 + \mathbf{q}_2 = (s_1 + s_2, \mathbf{v}_1 + \mathbf{v}_2)$$

$$\mathbf{q}_1 \cdot \mathbf{q}_2 = (s_1 s_2 - \mathbf{v}_1 \cdot \mathbf{v}_2, s_1 \mathbf{v}_2 + s_2 \mathbf{v}_1 + \mathbf{v}_1 \times \mathbf{v}_2)$$

$$\mathbf{q}_1^{-1} = (s_1, -\mathbf{v}_1) / (s_1^2 + |\mathbf{v}_1|^2) \Rightarrow \mathbf{q}_1 \mathbf{q}_1^{-1} = (1, \mathbf{0})$$

Unit quaternions

$q=(s, \mathbf{v})$

- $|q|^2 = s^2+|\mathbf{v}|^2$
- Unit quaternions satisfy $|q|^2 = 1$
- Represents the unit sphere in \mathbb{R}^4 , denoted S^3
- Any unit quaternion can be written

$q = (\cos \alpha/2, \sin \alpha/2 \mathbf{n})$ for some angle α and vector $|\mathbf{n}|=1$ (why?)

- In this case $q^{-1} = (\cos \alpha/2, -\sin \alpha/2 \mathbf{n})$

Quaternion representation of rotations

- Let $\mathbf{u} \in \mathbb{R}^3$ and represent it by the quaternion $p = (0, \mathbf{u})$
- Let $q = (\cos \alpha/2, \sin \alpha/2 \mathbf{n})$ be a unit quaternion
- Gives $q^{-1} = (\cos \alpha/2, -\sin \alpha/2 \mathbf{n})$
- Consider the quaternion product qpq^{-1}

$$p q^{-1} = (\sin \frac{\alpha}{2}(\mathbf{n} \cdot \mathbf{u}), \cos \frac{\alpha}{2} \mathbf{u} + \sin \frac{\alpha}{2}(\mathbf{n} \times \mathbf{u}))$$

Quaternion representation of rotations

- Finally, we get

$$qpq^{-1} = (\cos \frac{\alpha}{2}, \sin \frac{\alpha}{2} \mathbf{n}) \cdot (\sin \frac{\alpha}{2}(\mathbf{n} \cdot \mathbf{u}), \cos \frac{\alpha}{2} \mathbf{u} + \sin \frac{\alpha}{2}(\mathbf{n} \times \mathbf{u}))$$

$$qpq^{-1} = (0, \cos^2 \frac{\alpha}{2} \mathbf{u} + 2\cos \frac{\alpha}{2} \sin \frac{\alpha}{2}(\mathbf{n} \times \mathbf{u}) + \sin^2 \frac{\alpha}{2} \mathbf{n} \mathbf{n}^T \mathbf{u} + \sin^2 \frac{\alpha}{2} \mathbf{n} \times (\mathbf{n} \times \mathbf{u}))$$

$$qpq^{-1} = (0, \cos^2 \frac{\alpha}{2} \mathbf{u} + \sin \alpha [\mathbf{n}]_{\times} \mathbf{u} + \sin^2 \frac{\alpha}{2} (\mathbf{I} + [\mathbf{n}]_{\times}^2) \mathbf{u} + \sin^2 \frac{\alpha}{2} [\mathbf{n}]_{\times}^2 \mathbf{u})$$

$$qpq^{-1} = (0, \mathbf{u} + \sin \alpha [\mathbf{n}]_{\times} \mathbf{u} + (1 - \cos \alpha) [\mathbf{n}]_{\times}^2 \mathbf{u})$$

$$qpq^{-1} = (0, \mathbf{R}\mathbf{u})$$

Quaternion representation of rotations

Summary:

- We can represent points in \mathbb{R}^3 as "imaginary" quaternions p
- The rotation (α, \mathbf{n}) is represented as the unit quaternion $q=(\cos \alpha/2, \sin \alpha/2 \mathbf{n})$
- These consists of the set S^3
- The rotated point is computed as the *sandwich product* qpq^{-1}

Quaternion representation of rotations

- Composition of two rotations in standard 3×3 matrix algebra:
 - 27 mult
 - 18 add
- Composition of two rotations in quaternion algebra:
 - 16 mult
 - 12 add

The orthogonal Procrustes problem

- Given n known vectors \mathbf{a}_k and \mathbf{b}_k , which orthogonal \mathbf{R} minimizes

$$\sum_{k=1}^n \|\mathbf{a}_k - \mathbf{R}\mathbf{b}_k\|^2$$

The orthogonal Procrustes problem

Cookbook solution:

- See [Golub & Van Loan, *Matrix Computations*]
- Let \mathbf{A} be a matrix with all \mathbf{a}_k in its columns
- Let \mathbf{B} be a matrix with all \mathbf{b}_k in its columns
- $[\mathbf{U} \ \mathbf{S} \ \mathbf{V}] = \text{svd}(\mathbf{A} \mathbf{B}^T)$
- $\mathbf{R} = \mathbf{U} \mathbf{V}^T$
- Note: \mathbf{R} is in $O(3)$ but may not be in $SO(3)$!

Estimation of absolute orientation

- Given two set of n corresponding 3D points \mathbf{a}_k and \mathbf{b}_k that are related by a rigid transformation:

$$\mathbf{a}_k = \mathbf{R} \mathbf{b}_k + \mathbf{t}$$

How can we determine \mathbf{R} and \mathbf{t} ?

In particular when there is noise present?

Estimation of absolute orientation

- Let \mathbf{a}' and \mathbf{b}' denote the centroids of the set \mathbf{a}_k and the set \mathbf{b}_k , respectively:

$$\mathbf{a}' = \mathbf{R} \mathbf{b}' + \mathbf{t} \Rightarrow \mathbf{t} = \mathbf{a}' - \mathbf{R} \mathbf{b}'$$

- We need to find \mathbf{R} such that

$$\mathbf{a}_k - \mathbf{a}' = \mathbf{R} (\mathbf{b}_k - \mathbf{b}')$$

- \mathbf{R} can be found using the orthogonal Procrustes method
- Once \mathbf{R} is determined, \mathbf{t} is given by $\mathbf{a}' - \mathbf{R} \mathbf{b}'$
- See [Horn, *Closed-form solution of absolute orientation using unit Quaternions*, JOSA, 1987]