



Master in Computer Vision *Barcelona*

Module: 3D Vision

Lecture 4: Camera calibration. Pose estimation.

Lecturer: Gloria Haro

Outline

- Calibration
 - Camera resectioning
 - Calibration from a planar pattern
 - Image of the absolute conic
 - Camera distortion
- Pose estimation

Camera model

Remember:

$$\mathbf{x} \equiv P\mathbf{X}, \quad \mathbf{X} \in \mathbb{P}^3, \mathbf{x} \in \mathbb{P}^2,$$

where P is a 3×4 matrix, the **camera matrix**,

$$P = K [R | t]$$

$$\begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} = \begin{bmatrix} K_{11} & K_{12} & K_{13} \\ K_{21} & K_{22} & K_{23} \\ K_{31} & K_{32} & K_{33} \end{bmatrix} \begin{bmatrix} R_{11} & R_{12} & R_{13} & t_1 \\ R_{21} & R_{22} & R_{23} & t_2 \\ R_{31} & R_{32} & R_{33} & t_3 \end{bmatrix}$$

- ▶ K is the **calibration matrix** containing the **internal parameters** of the camera.
- ▶ R and t contain the **external parameters** of the camera: position and orientation of the camera in the reference system of the world (**camera pose**).

Calibration and pose estimation

- Calibration

$$P = \begin{bmatrix} ? & ? & ? & ? \\ ? & ? & ? & ? \\ ? & ? & ? & ? \end{bmatrix} \longrightarrow K$$

- Pose estimation

$$P = \begin{bmatrix} K_{11} & K_{12} & K_{13} \\ K_{21} & K_{22} & K_{23} \\ K_{31} & K_{32} & K_{33} \end{bmatrix} \begin{bmatrix} ? & ? & ? & ? \\ ? & ? & ? & ? \\ ? & ? & ? & ? \end{bmatrix}$$

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Camera resectioning

It uses a calibration object (or already reconstructed 3D points)

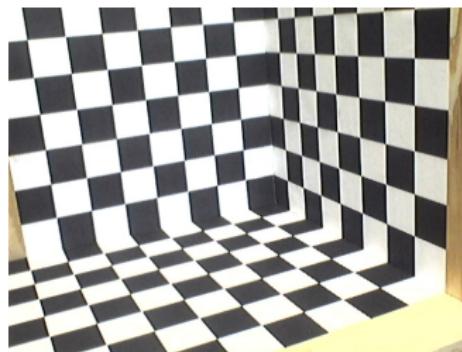


Image source: [B. Thibault]

for establishing a set of **3D to 2D point correspondences**

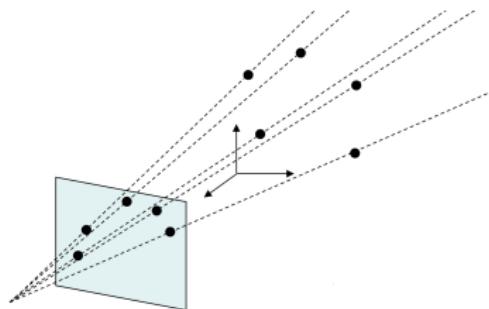


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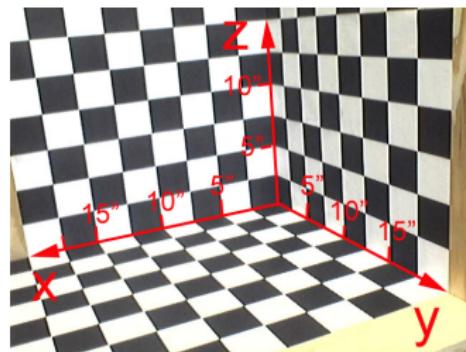


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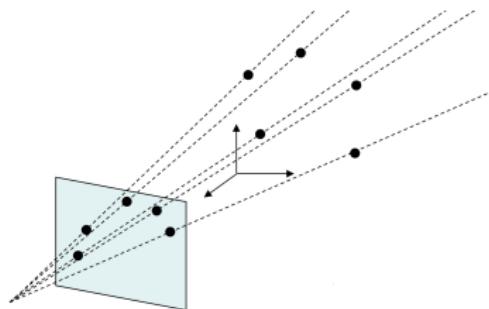


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Camera resectioning

From $N \geq 6$ known 3D to 2D point correspondences $\mathbf{X}_i \longleftrightarrow \mathbf{x}_i$

$$\mathbf{x}_i \equiv \mathbf{P} \mathbf{X}_i, \quad i = 1, 2, \dots, N \quad \text{where } \mathbf{x}_i \in \mathbb{P}^2, \mathbf{X}_i \in \mathbb{P}^3 \text{ are known.}$$

REMARK: As in DLT algorithm is important to previously normalize data, \mathbf{x}_i and \mathbf{X}_i , $i = 1, 2, \dots, N$.

By the same steps as for the DLT algorithm:

$$\begin{pmatrix} \mathbf{0}^T & -w_i \mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ w_i \mathbf{X}_i^T & \mathbf{0}^T & -x_i \mathbf{X}_i^T \end{pmatrix} \begin{pmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \mathbf{p}_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix},$$

$$\text{where } P = \begin{pmatrix} \mathbf{p}_1^T \\ \mathbf{p}_2^T \\ \mathbf{p}_3^T \end{pmatrix}_{3 \times 4}. \text{ Or, in short,}$$

$$\mathbf{A}_i \mathbf{p} = \mathbf{0}$$

(\mathbf{p} is the 12×1 vector of unknowns).

Camera resectioning

Each correspondence $\mathbf{X}_i \longleftrightarrow \mathbf{x}_i$
produces 2 equations for the 12 unknowns: $\mathbf{A}_i \mathbf{p} = \mathbf{0}$

As $P_{3 \times 4}$ has 11 degrees of freedom ($3 \times 4 - 1$ scale factor),
we need $N \geq 6$ correspondences $\mathbf{X}_i \longleftrightarrow \mathbf{x}_i$.

If \mathbf{A} denotes the matrix obtained by

$$\mathbf{A} = \begin{pmatrix} \mathbf{A}_1 \\ \dots \\ \mathbf{A}_N \end{pmatrix}_{2N \times 12}$$

with A_i the matrix of each correspondence $\mathbf{X}_i \longleftrightarrow \mathbf{x}_i$,
then the system of equations is

$$\mathbf{A} \mathbf{p} = \mathbf{0} \in \mathbb{R}^{2N}$$

The vector \mathbf{p} is in the null space of \mathbf{A} .

Camera resectioning

$$\mathbf{A}\mathbf{p} = \mathbf{0}$$

If the correspondences have noise, the identity is not satisfied and in practice we look for \mathbf{p} such that

$$\begin{aligned} & \min \|\mathbf{A}\mathbf{p}\| \\ & \text{such that } \|\mathbf{p}\|_2 = 1 \end{aligned}$$

We compute the solution by SVD :

$\mathbf{p} \equiv \text{last column of } \mathbf{V} \text{ in the SVD decomposition of } \mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}^T.$

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In presence of **outlier correspondences**
we may use the **RANSAC version of the DLT algorithm**

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This estimate may be refined by minimizing the geometric reprojection error: $\min \sum_i d(\mathbf{x}_i, P\mathbf{X}_i)^2$

Complete algorithm: Algorithm 7.1, Hartley-Zisserman book, page 181

Camera resectioning

Once P has been estimated, K , R , and \mathbf{t} may be extracted:

1. **QR factorization:** decomposition of the matrix A into a product $A = QR$, where Q is orthogonal, and R is an upper-triangular matrix.

$$\boxed{P} = (\boxed{Q} \boxed{R})^{-1} = \boxed{R}^{-1} \boxed{Q}^{-1}$$

$P = K[R | \mathbf{t}]$ where K is upper-triangular and R is orthogonal

QR decomposition of $P_{3 \times 3}$ gives K and R .

The ambiguity in the decomposition is removed by requiring that K have positive diagonal entries.

REMARK: RQ factorization may be also used.

Camera resectioning

Once P has been estimated, K , R , and \mathbf{t} may be extracted:

2. Case of zero skew:

$$A = P_{3 \times 3} P_{3 \times 3}^T = (KR)(KR)^T = KRR^T K = KK^T$$

$$\begin{bmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{bmatrix} = \begin{bmatrix} f_x & 0 & x_0 \\ 0 & f_y & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f_x & 0 & 0 \\ 0 & f_y & 0 \\ x_0 & y_0 & 1 \end{bmatrix} = \begin{bmatrix} f_x^2 + x_0^2 & x_0 y_0 & x_0 \\ x_0 y_0 & f_y^2 + y_0^2 & y_0 \\ x_0 & y_0 & 1 \end{bmatrix}$$

- Normalize $(P_{3 \times 3} P_{3 \times 3}^T)_{33} = A_{33} = 1$
- Identify parameters of K :

$$x_0 = A_{13}, \quad y_0 = A_{23}$$

$$f_x = \sqrt{A_{11} - x_0^2}, \quad f_y = \sqrt{A_{22} - y_0^2}$$

- Extract extrinsics (pose):

$$[R|\mathbf{t}] = K^{-1}P$$

REMARK: R may not be necessarily orthogonal, thus we further impose it.

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Calibration from a planar pattern (Zhang's method)



Z. Zhang. A Flexible New Technique for Camera Calibration. IEEE Trans. on Pattern Analysis and Machine Intelligence, 22 (11), 2000.

Calibration from a planar pattern (Zhang's method)



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1. Relation of a flat object and its image projection: H

$$\begin{bmatrix} \lambda u \\ \lambda v \\ \lambda \end{bmatrix} = \underbrace{\begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}}_H \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = [\mathbf{h}_1 \ \mathbf{h}_2 \ \mathbf{h}_3] \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$



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2. Flat object at plane $Z = 0$ projected to the image

$$\begin{bmatrix} \alpha u \\ \alpha v \\ \alpha \end{bmatrix} = K \underbrace{[\mathbf{r}_1 \ \mathbf{r}_2 \ \mathbf{r}_3 \ \mathbf{t}]}_R \begin{bmatrix} x \\ y \\ 0 \\ 1 \end{bmatrix}$$

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Calibration from a planar pattern

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H can be estimated, \mathbf{K} , \mathbf{r}_1 , \mathbf{r}_2 and \mathbf{t} are unknowns

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BUT, we know that \mathbf{r}_1 and \mathbf{r}_2 are columns of an orthogonal matrix

$$\left. \begin{array}{l} \mathbf{r}_1^T \mathbf{r}_2 = 0 \\ \mathbf{r}_1^T \mathbf{r}_1 = \mathbf{r}_2^T \mathbf{r}_2 = 1 \end{array} \right\} \quad (1)$$

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Isolating

$$[\mathbf{r}_1 \ \mathbf{r}_2 \ \mathbf{t}] \sim [K^{-1}\mathbf{h}_1 \ K^{-1}\mathbf{h}_2 \ K^{-1}\mathbf{h}_3]$$

Calibration from a planar pattern

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Applying (1)

$$\left. \begin{array}{l} \mathbf{h}_1^T K^{-T} K^{-1} \mathbf{h}_2 = 0 \\ \mathbf{h}_1^T K^{-T} K^{-1} \mathbf{h}_1 = \mathbf{h}_2^T K^{-T} K^{-1} \mathbf{h}_2 \end{array} \right\}$$

Calibration from a planar pattern

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where $\omega = (KK^T)^{-1} = K^{-T}K^{-1}$ is the **Image of the Absolute Conic**

Calibration from a planar pattern

We have

$$\left. \begin{array}{l} \mathbf{h}_1^T \omega \mathbf{h}_2 = 0 \\ \mathbf{h}_1^T \omega \mathbf{h}_1 = \mathbf{h}_2^T \omega \mathbf{h}_2 \end{array} \right\}$$

$\omega = (KK^T)^{-1} = K^{-T}K^{-1}$ is a symmetric matrix

$$\omega = \begin{pmatrix} \omega_{11} & \omega_{12} & \omega_{13} \\ \omega_{12} & \omega_{22} & \omega_{23} \\ \omega_{13} & \omega_{23} & \omega_{33} \end{pmatrix}$$

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Calibration from a planar pattern

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Calibration from a planar pattern

$$\mathbf{h}_i^T \omega \mathbf{h}_j^T = (h_{1i} \ h_{2i} \ h_{3i}) \begin{pmatrix} \omega_{11} & \omega_{12} & \omega_{13} \\ \omega_{12} & \omega_{22} & \omega_{23} \\ \omega_{13} & \omega_{23} & \omega_{33} \end{pmatrix} \begin{pmatrix} h_{1j} \\ h_{2j} \\ h_{3j} \end{pmatrix} = \mathbf{V}_{ij}^T \Omega$$

where $\mathbf{V}_{ij}^T =$

$$(h_{1i} \ h_{1j}, \ h_{1i} \ h_{2j} + h_{2i} \ h_{1j}, \ h_{1i} \ h_{3j} + h_{3i} \ h_{1j}, \ h_{2i} \ h_{2j}, \ h_{2i} \ h_{3j} + h_{3i} \ h_{2j}, \ h_{3i} \ h_{3j})$$

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Then

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Calibration from a planar pattern

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2 equations for 6 unknowns \rightarrow we need $n = 3$ views (homographies) to find ω

We have to solve

$$V_{2n \times 6} \Omega = \mathbf{0}$$

Calibration from a planar pattern

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REMARK: if we use additional constraints on K

- zero skew \rightarrow we need $n = 2$ views
- zero skew and known principal point \rightarrow we need $n = 1$ view

Calibration from a planar pattern

We have to solve

$$V \Omega = \mathbf{0}$$

In practice we solve:

$$\min_{\Omega} \|V \Omega\|_2$$

$$\text{such that } \|\Omega\|_2 = 1$$

SOLUTION: Ω is the singular vector associated to the smallest singular value (last column of \bar{U} , where $V = \underset{\text{SVD}}{UD\bar{U}^T}$)

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$$V \xrightarrow{\text{SVD}} \Omega \xrightarrow{\text{rearrangement}} \omega = K^{-T} K^{-1} \xrightarrow{\text{Cholesky}} K$$

Calibration from a planar pattern

How to find R and t (pose) from K ?

Calibration from a planar pattern

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We have

$$[\mathbf{r}_1 \mathbf{r}_2 \mathbf{t}] \sim [K^{-1} \mathbf{h}_1 K^{-1} \mathbf{h}_2 K^{-1} \mathbf{h}_3]$$

and since $\|\mathbf{r}_1\| = \|\mathbf{r}_2\| = 1$,

then,

$$\mathbf{r}_1 = \frac{K^{-1}\mathbf{h}_1}{\|K^{-1}\mathbf{h}_1\|}, \quad \mathbf{r}_2 = \frac{K^{-1}\mathbf{h}_2}{\|K^{-1}\mathbf{h}_2\|}, \quad \mathbf{r}_3 = \mathbf{r}_1 \times \mathbf{r}_2$$

$$\mathbf{t} = \frac{K^{-1}\mathbf{h}_3}{\|K^{-1}\mathbf{h}_1\|}$$

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$$\mathbf{r}_1 = \frac{K^{-1}\mathbf{h}_1}{\|K^{-1}\mathbf{h}_1\|}, \quad \mathbf{r}_2 = \frac{K^{-1}\mathbf{h}_2}{\|K^{-1}\mathbf{h}_2\|}, \quad \mathbf{r}_3 = \mathbf{r}_1 \times \mathbf{r}_2$$

$$\mathbf{t} = \frac{K^{-1}\mathbf{h}_3}{\|K^{-1}\mathbf{h}_1\|}$$

BUT, not guarantee (noise) that $R = (\mathbf{r}_1 \mathbf{r}_2 \mathbf{r}_3)$ is an orthogonal matrix.

Calibration from a planar pattern

How to find R and t (pose) from K ?

We have

$$[\mathbf{r}_1 \mathbf{r}_2 \mathbf{t}] \sim [K^{-1}\mathbf{h}_1 K^{-1}\mathbf{h}_2 K^{-1}\mathbf{h}_3]$$

and since $\|\mathbf{r}_1\| = \|\mathbf{r}_2\| = 1$,

then,

$$\mathbf{r}_1 = \frac{K^{-1}\mathbf{h}_1}{\|K^{-1}\mathbf{h}_1\|}, \quad \mathbf{r}_2 = \frac{K^{-1}\mathbf{h}_2}{\|K^{-1}\mathbf{h}_2\|}, \quad \mathbf{r}_3 = \mathbf{r}_1 \times \mathbf{r}_2$$

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BUT, not guarantee (noise) that $R = (\mathbf{r}_1 \mathbf{r}_2 \mathbf{r}_3)$ is an orthogonal matrix.
THEN, we impose it:

$$\tilde{R} = U \bar{U}^T$$

where $R \underset{SVD}{=} U D \bar{U}^T$.

Calibration from a planar pattern

Steps of the calibration algorithm

- Estimate the n homographies that relate the planar pattern and the n images.
- Build matrix V .
- Find ω by solving the SVD of V .
- Extract calibration parameters, K , by Cholesky factorization of ω .
- (Optional) Extract pose, R and t .
- (Optional) Refinement by minimizing the geometric error

Outline

- Calibration
 - Camera resectioning
 - Calibration from a planar pattern
 - [Image of the absolute conic](#)
 - Camera distortion
- Pose estimation

Image of the absolute conic

The **absolute conic**, Ω_∞ , is a conic on the plane at infinity, Π_∞ .

It consists of points $X = (\underbrace{x_1, x_2, x_3}_\mathbf{d}, 0)^T$ such that $x_1^2 + x_2^2 + x_3^2 = 0$.

In matricial form: $\mathbf{d}^T / \mathbf{d} = 0$, then

$$\Omega_\infty = I_{3 \times 3}$$

PROPERTY: The absolute conic remains fixed by a similarity.

Image of the absolute conic

REMARK: Ω_∞ is defined in an Euclidean frame, then if we change coordinates to a projective frame the image of Ω_∞ will be, in general, a finite conic represented by matrix ω .

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Points on Ω_∞ : $\begin{pmatrix} \mathbf{d} \\ 0 \end{pmatrix}$

Their image (camera projection) is:

$$P \begin{pmatrix} \mathbf{d} \\ 0 \end{pmatrix} = K[R \; \mathbf{t}] \begin{pmatrix} \mathbf{d} \\ 0 \end{pmatrix} = KR\mathbf{d} = \mathbf{x}$$

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$H = KR$ is the (2D) homography that relates Π_∞ and the image plane.

Image of the absolute conic

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Remember how a conic is transformed by a homography: $C' = H^{-T}CH^{-1}$

Then,

$$(KR)^{-T} I (KR)^{-1} = K^{-T} \underbrace{RR^{-1}}_I K^{-1} = K^{-T} K^{-1} = (KK^T)^{-1} = \omega$$

Image of the absolute conic

REMARKS:

- ω depends only on the internal parameters of the camera, K .
- ω allows to measure angles in 3D world from image points.

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If \mathbf{d}_1 and \mathbf{d}_2 are the directions of two lines in \mathbb{R}^3 , the angle θ they form satisfies:

$$\cos \theta = \frac{\mathbf{d}_1^T \mathbf{d}_2}{\sqrt{\mathbf{d}_1^T \mathbf{d}_1} \sqrt{\mathbf{d}_2^T \mathbf{d}_2}} = \frac{\mathbf{d}_1^T \Omega_\infty \mathbf{d}_2}{\sqrt{\mathbf{d}_1^T \Omega_\infty \mathbf{d}_1} \sqrt{\mathbf{d}_2^T \Omega_\infty \mathbf{d}_2}}$$

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Since their points at infinity are $(\mathbf{d}_1^T, 0)^T$ and $(\mathbf{d}_2^T, 0)^T$, their image projections (vanishing points) are:

$$\mathbf{x}_1 = KR\mathbf{d}_1 \text{ and } \mathbf{x}_2 = KR\mathbf{d}_2$$

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We have that:

$$\mathbf{d}_i^T \Omega_\infty \mathbf{d}_j = \mathbf{x}_i^T (KR)^{-T} \Omega_\infty (KR)^{-1} \mathbf{x}_j = \mathbf{x}_i^T \omega \mathbf{x}_j, \text{ for } i, j \in \{1, 2\}$$

Image of the absolute conic

Then,

$$\cos \theta = \frac{\mathbf{x}_1^T \omega \mathbf{x}_2}{\sqrt{\mathbf{x}_1^T \omega \mathbf{x}_1} \sqrt{\mathbf{x}_2^T \omega \mathbf{x}_2}}$$

where \mathbf{x}_1 and \mathbf{x}_2 are two vanishing points.

Image of the absolute conic

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In particular, for **orthogonal directions**

$$\mathbf{x}_1^T \omega \mathbf{x}_2 = 0$$

It provides a constraint on ω (K)

Image of the absolute conic

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$$\cos \theta = \frac{\mathbf{x}_1^T \omega \mathbf{x}_2}{\sqrt{\mathbf{x}_1^T \omega \mathbf{x}_1} \sqrt{\mathbf{x}_2^T \omega \mathbf{x}_2}}$$

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In particular, for **orthogonal directions**

$$\mathbf{x}_1^T \omega \mathbf{x}_2 = 0$$

It provides a constraint on $\omega (K)$ → **Useful for self-calibration!**

Outline

- Calibration
 - Camera resectioning
 - Calibration from a planar pattern
 - Image of the absolute conic
 - [Camera distortion](#)
- Pose estimation

Camera distortion

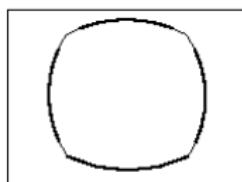
Pinhole cameras: linear model of the imaging process

Real (non-pinhole) cameras: lens distortion (non-linear), usually radial distortion



short vs long focal length

radial distortion



→
correction

linear image

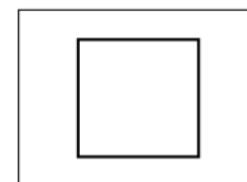
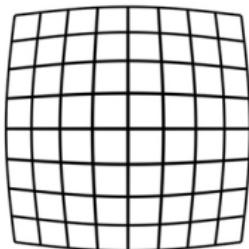


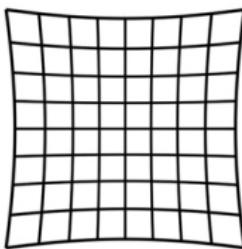
Image source: [Hartley and Zisserman 2004]

Camera distortion

Radial distortion



Barrel Distortion



Pincushion Distortion



Barrel and Pincushion examples

Coordinates in the observed image are displaced away, **barrel distortion**, or towards, **pincushion distortion**, the image center by an amount proportional to their radial distance.

$$x_d = L(r) x = (1 + k_1 r + k_2 r^2 + k_3 r^3 + \dots) x$$

$$y_d = L(r) y = (1 + k_1 r + k_2 r^2 + k_3 r^3 + \dots) y$$

$$\text{where } r = \sqrt{x^2 + y^2}$$

Image source: [Szeliski 2010]

Camera distortion

How to estimate the distortion parameters:

- **Plumb-line method**, adjust parameters k_i so that images of straight lines become straight in the image.



- Parameters k_i are estimated jointly with those of P by **iterative minimization of a geometric error**.

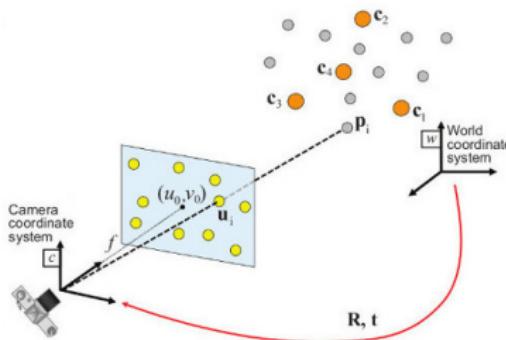
$$\min \sum_i \sum_j \| \mathbf{x}_{ij} - f(k_1, k_2, \dots, k_n, K, R_i, \mathbf{t}_i, \mathbf{X}_j) \|_2^2$$

Outline

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Pose estimation

Estimate camera pose from n 3D-to-2D point correspondences.



If we assume known calibration parameters, K , the problem is called **Perspective-n-Point (PnP)** problem

$$P = \begin{bmatrix} K_{11} & K_{12} & K_{13} \\ K_{21} & K_{22} & K_{23} \\ K_{31} & K_{32} & K_{33} \end{bmatrix} \begin{bmatrix} ? & ? & ? & ? \\ ? & ? & ? & ? \\ ? & ? & ? & ? \end{bmatrix}$$

Only R and t (6 dof) need to be determined.

Image source: [\[https://docs.opencv.org\]](https://docs.opencv.org)

PnP methods

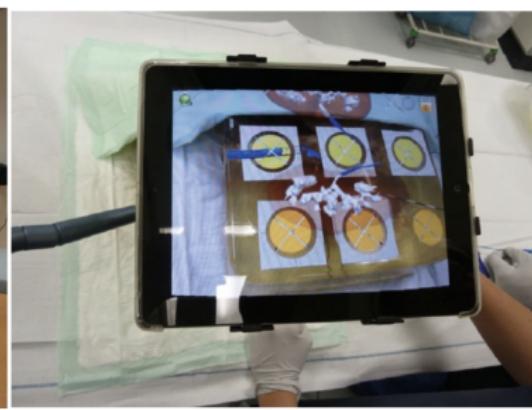
PnP problem: Estimate the absolute pose of a calibrated camera

Data: n 3D-2D point correspondences + camera internal parameters K

Goal: estimate camera pose, R and t

Applications:

localization of robots and object manipulation, augmented reality, ...



Collet et al. Object Recognition and Full Pose Registration from a Single Image for Robotic Manipulation. In Proc. of IEEE Int. Conf. on Robotics and Automation (ICRA), 2009.

Müller et al. Mobile augmented reality for computer-assisted percutaneous nephrolithotomy. International journal of computer assisted radiology and surgery, 2013.

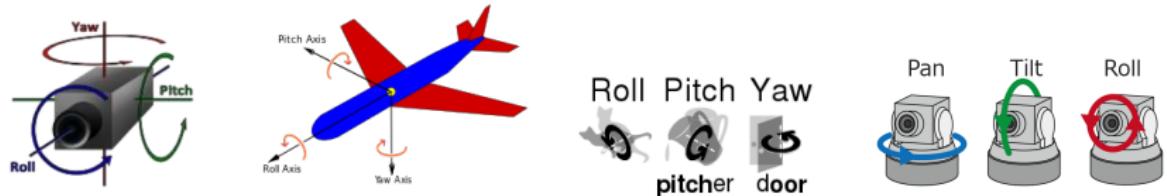
PnP methods

Different methods (according to n):

- P3P [1,2]
- P4P [3,4]
- P5P [4]
- PnP methods
 - iterative (geometric or algebraic errors) → accurate but sensitive to local minima
 - non-iterative → no local minima
 - ▶ EPnP [5] (1st efficient non-iterative solution for large n)
 - ▶ RPnP [6]
 - ▶ ASPnP [7]
 - ▶ OPnP [8]
 - ▶ Robustified EPnP [9] → fast, accurate, robust to outliers

- [1] D. DeMenthon, L. Davis. Exact and approximate solutions of the perspective-three-point problem. PAMI 14(11), 1992.
- [2] L. Kneip, D. Scaramuzza, R. Siegwart. A novel parametrization of the perspective-three-point problem for a direct computation of absolute camera position and orientation. CVPR, 2011.
- [3] M.A. Fischler and R.C. Bolles. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM, 1981.
- [4] B. Triggs. Camera pose and calibration from 4 or 5 known 3D points. ICCV, 1999.
- [5] F. Moreno-Noguer, V. Lepetit, P. Fua. Accurate non-iterative $O(n)$ solution to the PnP problem. ICCV 2007.
- [6] S. Li, C. Xu, M. Xie. A robust $O(n)$ solution to the perspective-n-point problem. PAMI 34(7), 2012.
- [7] Y. Zheng, S. Sugimoto, M. Okutomi. AsPnP: An accurate and scalable solution to the perspective-n-point problem. Trans. on Information and Systems, 96(7), 2013.
- [8] Y. Zheng, Y. Kuang, S. Sugimoto, K. Aström, M. Okutomi. Revisiting the PnP problem: A fast, general and optimal solution. ICCV, 2013.
- [9] L. Ferraz, X. Binefa, F. Moreno-Noguer. Very fast solution to the PnP problem with algebraic outlier rejection. CVPR 2014.

Pose estimation: camera orientation



Vanishing lines and pose orientation

- Horizon
- Camera roll angle (tilted toward right): horizon angle
- Camera pitch (tilt) angle (looking down): horizon offset



Camera parameters and vanishing points



$$\alpha Z = \frac{-\|\mathbf{b} \times \mathbf{t}\|}{(\hat{\mathbf{l}} \cdot \mathbf{b})\|\mathbf{v} \times \mathbf{t}\|}$$

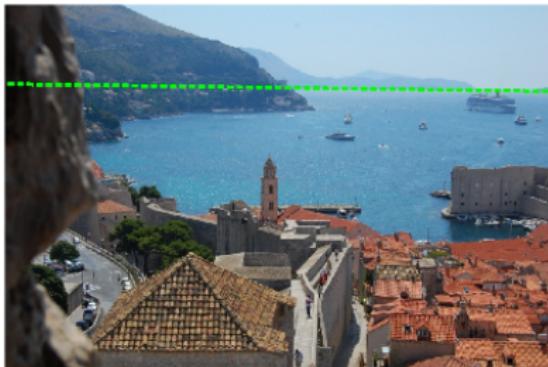
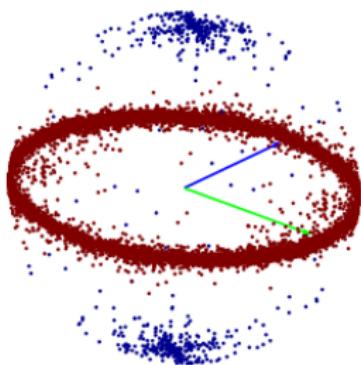


A. Criminisi, I. Reid and A. Zisserman, Single view metrology, IEEE International Conference on Computer Vision (ICCV), 1999.

Pose estimation with deep learning

Horizon lines in the wild

<http://hlw.csr.uky.edu>



Workman S., Zhai M., Jacobs N. Horizon Lines in the Wild. In: British Machine Vision Conference (BMVC), 2016

Pose estimation with deep learning

Estimation of roll, pitch and focal length

- Calibration
- Image retrieval



Query



NN1



NN2



NN3



NN4

- Geometrically-consistent object transfer
- Virtual object insertion



Y. Hold-Geoffroy, K. Sunkavalli, J. Eisenmann, M. Fisher, E. Gambaretto, S. Hadap, and J.-F. Lalonde, A Perceptual Measure for Deep Single Image Camera Calibration, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018.

Pose estimation with deep learning

Estimation of roll, pitch, focal length and radial distortion



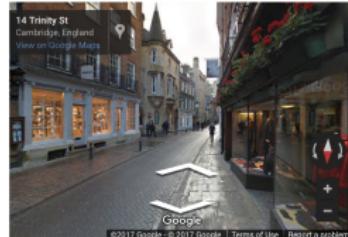
M. López-Antequera, R. Mari, P. Gargallo, Y. Kuang, J. Gonzalez-Jimenez, G. Haro, Deep Single Image Camera Calibration with Radial Distortion, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019.

Pose estimation with deep learning

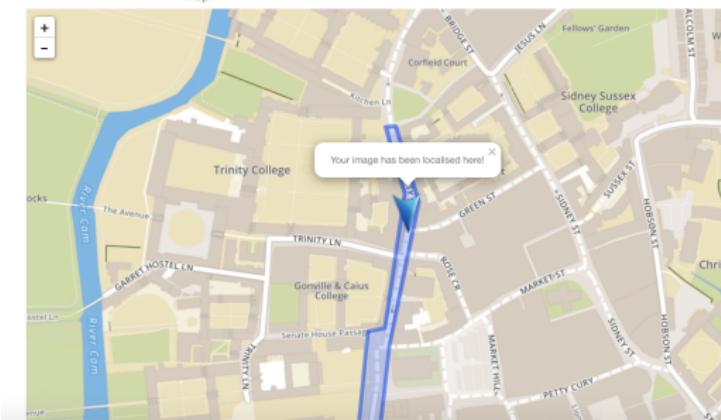
<http://mi.eng.cam.ac.uk/projects/relocalisation>



We have localised your input image on the map below! The blue arrow shows where we think you are. The image must have been taken within the blue highlighted region on the map.



This is the closest view in Google Maps Street View to the blue arrow.



Posenet: estimates 3D position and orientation of the camera given a single monocular image taken from a large previously explored scene.

Summary

We have seen:

- Camera calibration
- Image of the absolute conic
- Pose estimation

Summary

We have seen:

- Camera calibration
- Image of the absolute conic
- Pose estimation

Next class:

- The geometry of two views

References

- [Hartley and Zisserman 2004] R.I. Hartley and A. Zisserman, Multiple View Geometry in Computer Vision, Cambridge University Press, 2004.
- [Szeliski 2010] R. Szeliski, Computer Vision: Algorithms and Applications, Springer, 2010.