

## CIS 580

## HOMOGENEOUS

## Point (3D)

Finite  $(X, Y, Z) \rightarrow (X, Y, Z, 1)$ Infinite  $(\infty, 0, 0, 1) \rightarrow (1, 0, 0, 0)$  $(X, Y, Z) \rightarrow \lambda(x, y, 1)$ Point (2D)  $(x, y) \rightarrow (x, y, 1)$ Line (2D)  $ax + by + c = 0 \rightarrow (a, b, c)$ 

## CAMERA MODEL

## 3D-2D PROJECTION

 $(u_{ccd}, v_{ccd}) = (f_{mx} X/Z, f_{my} Y/Z)$  $u_{img} = u_{ccd} \frac{w_{img}}{w_{ccd}} + p_x = f_x \frac{x}{z} + p_x$  $v_{img} = v_{ccd} \frac{h_{img}}{h_{ccd}} + p_y = f_y \frac{y}{z} + p_y$ where  $f_x = f_{mx} \frac{w_{img}}{w_{ccd}}, f_y = f_{my} \frac{h_{img}}{h_{ccd}}$ 

$$\lambda \begin{bmatrix} u_{img} \\ v_{img} \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & p_x \\ 0 & f_y & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

## Related topics

- 2d inverse projection
- Dolly zoom: change  $f$  and  $Z$  at the same time to keep object size on image the same
- Locate center of projection

## CAMERA PROJECTION

$$\lambda \begin{bmatrix} u_{img} \\ v_{img} \\ 1 \end{bmatrix} = L K \begin{bmatrix} R & T \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

## ORTHOGRAPHIC CAMERA

## Affine camera

$$P_A = \begin{bmatrix} f_x & 0 & p_x \\ 0 & f_y & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{x1} & r_{x2} & 0 & 0 \\ r_{y1} & r_{y2} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Orthographic camera  $K = I$ 

$$P_o = \begin{bmatrix} r_{x1} & r_{x2} & r_{x3} & 0 \\ r_{y1} & r_{y2} & r_{y3} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

## PROJECTIVE LINE

## VANISHING POINTS &amp; LINES

## Information provided by vanishing lines

- Horizon
- Camera pitch angle
- Camera roll angle

## Routine to compute vanishing line (2D)

- line through two points:  $l = x_1 \times x_2$
- Vanishing point - intersection of two lines which are parallel in 3D space (need rescale):  $x = l_1 \times l_2$
- Vanishing line through two points  $v_1, v_2$ :  $l_v = v_1 \times v_2$

## From 2D to 3D

- A 2D line in an image corresponds to a 3D plane passes the camera center of normal:  $\lambda \hat{l} =$

$$(\lambda_1 K^{-1} x_1) \times (\lambda_2 K^{-1} x_2)$$

- The intersection point of two lines corresponds to a 3D ray passes the camera center  $\hat{x} = \hat{l}_1 \times \hat{l}_2$

## TRANSFORMATION OF POINT AND LINE

$$x' = Hx, l' = (H^{-1})^T l$$

Infinite point/line becomes finite after projective transformation:

$$\begin{bmatrix} x'_1 \\ x'_2 \\ x'_3 \end{bmatrix} = H \begin{bmatrix} x_1 \\ x_2 \\ 0 \end{bmatrix}, \begin{bmatrix} l'_1 \\ l'_2 \\ l'_3 \end{bmatrix} = H^{-T} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

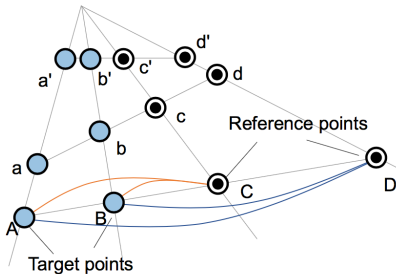
## INFINITY

A point at infinity = a direction  $x_\infty = (a \ b \ 0)^T$ All points at infinity lie in the line at infinity  $l_\infty = (0 \ 0 \ 1)^T = Z$ 

## SINGLE VIEW METROLOGY

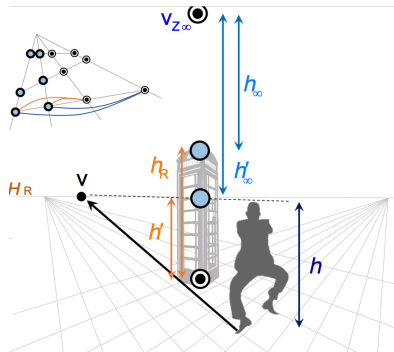
Camera height – where the horizon is  $h = fH/Z$ 

## CROSS RATIO



$$\frac{ACBD}{BCAD} = \frac{acbd}{bcad} = \frac{a'c'b'd'}{b'c'a'd'}$$

Reference points: bottom and infinity



$$\frac{h_r}{H} \frac{h_c}{h_v} = \frac{H_r}{H} \frac{H_c}{H_v} = \frac{H_r}{H} \frac{\infty}{\infty} = \frac{H_r}{H}$$

Given image and  $H_a$ , estimate  $H_b$ Compute vanishing line  $l_v$ 

$$v = (a_f \times b_f) \times l_v$$

$$b'_h = (v \times b_h) \times (a_f \times a_h)$$

compute vanishing point in vertical  $v_{z\infty}$ 

$$H_b = H_a \frac{\|b'_h - a_f\|}{\|a_h - a_f\|} \frac{\|v_{z\infty} - a_h\|}{\|v_{z\infty} - b'_h\|}$$

## SINGLE VIEW

VANISHING POINT  $\rightarrow$  CAMERA ROT

$$r_3 = K^{-1} v_{z\infty} / \|K^{-1} v_{z\infty}\|$$

$$\beta = \tan^{-1}(-r_{31} / \sqrt{r_{32}^2 + r_{33}^2})$$

$$\gamma = \tan^{-1}(r_{32} / r_{33})$$

Or

$$r_1 = K^{-1} v_{x\infty} / \|K^{-1} v_{x\infty}\|$$

$$r_2 = K^{-1} v_{y\infty} / \|K^{-1} v_{y\infty}\|$$

$$r_3 = r_1 \times r_2$$

## SINGLE-VIEW HOMOGRAPHY

“2D”  $\rightarrow$  2D: take points on plane  $Z = 0$ 

$$\lambda x = HX = K[r_1 \ r_2 \ t]X$$

Homography estimation using 4s points

$$\begin{bmatrix} X^T & 0_{1 \times 3} & -U X^T \\ 0_{1 \times 3} & X^T & -V X^T \end{bmatrix} \begin{bmatrix} h_1^T \\ h_2^T \\ h_3^T \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$r_1 = K^{-1} H_1 / \|K^{-1} H_1\|$$

$$r_2 = K^{-1} H_2 / \|K^{-1} H_1\|$$

$$r_3 = r_1 \times r_2$$

$$t = r_2 = K^{-1} H_3 / \|K^{-1} H_1\|$$

two configurations, choose the one where points are before the camera

## CAMERA CALIBRATION

## INTRINSIC BIAS

Scale factor; image center position; skew factor; lens distortion

## SINGLE VIEW CALIBRATION

## “Guessing”

Change  $f$  (or  $K$ ) each time; Repeat:

Compute vanishing point at

$$X_\infty, Y_\infty: V_1, V_2$$

$$r_1 = K^{-1} V_1 / \|K^{-1} V_1\|$$

$$r_2 = K^{-1} V_2 / \|K^{-1} V_2\|$$

$$r_3 = r_1 \times r_2$$

$$R = [r_1 \ r_2 \ r_3]$$

Until  $R$  is orthogonal

## Calibration using vanishing pts

[Angle between vanishing points]

If we know the angle between two vanishing points in 3D, we can estimate  $K$  via:

$$\cos \theta = \frac{x_1^T (K^{-1} K^{-1})^T x_2}{\sqrt{x_1^T (K^{-1} K^{-1}) x_1} \sqrt{x_2^T (K^{-1} K^{-1}) x_2}}$$

[Use vanishing points in  $X, Y, Z$ ]

$$(K^{-1} v_{x\infty})^T (K^{-1} v_{y\infty}) = (K^{-1} v_{x\infty})^T (K^{-1} v_{z\infty}) = (K^{-1} v_{y\infty})^T (K^{-1} v_{x\infty}) = 0$$

$$(K^{-1} v_i)^T (K^{-1} v_j) = v_i^T K^{-1} K^{-1} v_j \quad i, j = X, Y, Z, \text{ and } i \neq j$$

$$b_1 = \frac{1}{f^2}, \quad b_2 = -\frac{p_x}{f^2}, \quad b_3 = -\frac{p_y}{f^2}, \quad b_4 = \frac{p_x^2}{f^2} + \frac{p_y^2}{f^2} + 1$$

$$\begin{bmatrix} u_1 u_2 + v_1 v_2 & u_1 + u_2 & v_1 + v_2 & 1 \\ u_3 u_2 + v_3 v_2 & u_3 + u_2 & v_3 + v_2 & 1 \\ u_1 u_3 + v_1 v_3 & u_1 + u_3 & v_1 + v_3 & 1 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix} = 0$$

$$p_x = -\frac{b_2}{b_1}, \quad p_y = -\frac{b_3}{b_1}, \quad f = \sqrt{\frac{b_4}{b_1} - (p_x^2 + p_y^2)}$$

## SINGLE VIEW CALIBRATION

## Checkerboard method (Project 1)

- Compute homography matrices from checkerboard plane to image plane

$$H = K[r_1 \ r_2 \ t]$$

- Recover  $K$  from all  $H$ s

$$K^{-T}K^{-1} = \begin{bmatrix} \frac{1}{f_x^2} & -\frac{p_x}{f_x^2} & \frac{p_x^2 - p_y^2}{f_x^2} \\ -\frac{p_x}{f_x^2} & \frac{1}{f_y^2} & -\frac{p_x p_y}{f_x^2 f_y^2} \\ \frac{p_x^2 - p_y^2}{f_x^2} & -\frac{p_x p_y}{f_x^2 f_y^2} & \frac{p_y^2}{f_y^2} + 1 \end{bmatrix} = \begin{bmatrix} B_{11} & B_{12} & B_{13} \\ B_{21} & B_{22} & B_{23} \\ B_{31} & B_{32} & B_{33} \end{bmatrix} = B.$$

$$p_y = \frac{B_{12}B_{13} - B_{11}B_{23}}{B_{11}B_{22} - B_{12}^2} \quad f_x = \sqrt{\frac{c}{B_{11}}} \\ c = B_{33} - \frac{B_{13}^2 + p_y(B_{12}B_{13} - B_{11}B_{23})}{B_{11}} \quad s = -\frac{B_{12}f_x^2 f_y}{c} \\ f_y = \sqrt{\frac{cB_{11}}{B_{11}B_{22} - B_{12}^2}} \quad p_x = \frac{sp_y}{f_y} - \frac{B_{13}f_x^2}{c}.$$

$$\begin{bmatrix} {}^1v_{11}^T & -{}^1v_{12}^T \\ {}^1v_{12}^T & -{}^1v_{22}^T \\ \vdots & \vdots \\ {}^Nv_{11}^T & -{}^Nv_{12}^T \\ {}^Nv_{12}^T & -{}^Nv_{22}^T \end{bmatrix} \begin{bmatrix} B_{11} \\ B_{12} \\ B_{22} \\ B_{13} \\ B_{23} \\ B_{33} \end{bmatrix} = 0 \quad v_{ij} = \begin{bmatrix} h_{11}h_{j1} \\ h_{11}h_{j2} + h_{12}h_{j1} \\ h_{12}h_{j2} \\ h_{13}h_{j1} + h_{11}h_{j3} \\ h_{13}h_{j2} + h_{12}h_{j3} \\ h_{13}h_{j3} \end{bmatrix}$$

- Estimate transformations

$$\mathbf{r}_1 = \frac{1}{z'} K^{-1} \mathbf{h}_1 \quad \mathbf{r}_3 = \mathbf{r}_1 \times \mathbf{r}_2 \\ \mathbf{r}_2 = \frac{1}{z'} K^{-1} \mathbf{h}_2 \quad \mathbf{t} = \frac{1}{z'} K^{-1} \mathbf{h}_3,$$

- Estimate radial distortion

$$\bar{\mathbf{u}}_{\text{distorted}} = K^{-1} \mathbf{u}_{\text{distorted}} \quad \bar{\mathbf{u}}_{\text{undistorted}} = K^{-1} \mathbf{u}_{\text{undistorted}} \\ \bar{\mathbf{u}}_{\text{distorted}} = (1 + k_1 \rho^2 + k_2 \rho^4) \bar{\mathbf{u}}_{\text{undistorted}}$$

$$\begin{bmatrix} \rho^2 \bar{\mathbf{u}}_{\text{undistorted}}^1 & \rho^4 \bar{\mathbf{u}}_{\text{undistorted}}^1 \\ \vdots & \vdots \\ \rho^2 \bar{\mathbf{u}}_{\text{undistorted}}^m & \rho^4 \bar{\mathbf{u}}_{\text{undistorted}}^m \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \end{bmatrix} = \begin{bmatrix} \bar{\mathbf{u}}_{\text{distorted}}^1 - \bar{\mathbf{u}}_{\text{undistorted}}^1 \\ \vdots \\ \bar{\mathbf{u}}_{\text{distorted}}^m - \bar{\mathbf{u}}_{\text{undistorted}}^m \end{bmatrix}$$

- Define geometric error and run optimization on the estimated initial parameters

## TWO VIEW GEOMETRY

In the following topics, define  $P_1 = K_1[I_{3 \times 3} \quad 0_{3 \times 1}]$ ,  $P_2 = K_2[R \quad t]$   
 $C = -R^T t$ ,  $P_2 = K_2 R[I_{3 \times 3} \quad -C]$   
 $x^+$ ,  $X^+$  - homogeneous form of  $x$ ,  $X$

## EPIPOLE AND EPIPOLAR LINE

- Epipolar constraints between two images:  $x_1$  in image 1 correspond to an epipolar line in image 2 (vice versa)
- the epipolar line  $l_{x_1}$  passes corresponding point  $x_2$  in image 2
- any point along the epipolar line can be a candidate of correspondence
- epipolar lines meet at epipole
- pure rotation: no epipolar constraint;
- pure translation: stereo

**Compute epipoles**

$$\lambda e_1 = P_1 \begin{bmatrix} -R^T t \\ 1 \end{bmatrix} = -K_1 R^T t$$

$$\lambda e_2 = P_2 \begin{bmatrix} 0 \\ 1 \end{bmatrix} = K_2 t$$

**Compute epipolar lines** see below

## FUNDAMENTAL MATRIX

$$F = K_2^{-T}(t \times R)K_1^{-1}, \quad x_1^T F x_2 = 0$$

This fundamental matrix transform image 1's space to image 2's space.

$\tilde{F} = K_1^{-T}(R \times t)K_2^{-1} = F^T$ ,  $x_1^T \tilde{F} x_2 = 0$   
 $\text{rank}(F)=2$ ,  $\text{DOF} = 7$ , requires at least 4 pairs of points to estimate

**SVD clean up** set the last eigenvalue 0

**F vs epipolar line**  $l_{x_1} = F x_1$ ,  $l_{x_2} = F^T x_2$

$$(x_2^T l_{x_1} = 0, l_{x_2}^T x_1 = 0)$$

**F vs epipole**  $F e_1 = 0$ ,  $F^T e_2 = 0$

$e_1 = \text{null}(F)$ ,  $e_2 = \text{null}(F^T)$

## ESSENTIAL MATRIX

$$F = K_2^{-T}(t \times R)K_1^{-1} = K_2^{-T} E K_1^{-1}$$

$$E = (t \times R) = K_2^T F K_1, \quad X_2^T E X_1 = 0$$

**SVD clean up** set the last eigenvalue 0

This essential matrix transform camera 1's space to camera 2's space.

**Recover R, t from E**

$$\text{SVD: } E = U D V^T, \quad U = [u_1 \quad u_2 \quad u_3]$$

$$t = \pm \text{null}(E) = \pm u_1 \times u_2 = \pm u_3$$

$$R = U \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} V^T, \text{ or } U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} V^T$$

Select the best configuration out of four

## LINEAR ESTIMATION

$$Ax = b$$

Minimize  $E = \|Ax - b\|^2$

$$E = x^T A^T A x - 2x^T A^T b + b^T b$$

$$\frac{\partial E}{\partial x} = 2(A^T A x - A^T b) = 0$$

$$x = (A^T A)^{-1} A^T b$$

**Application:** line fitting, circle fitting

**Properties:** convex, closed form, efficient, no extra parameters

$$Ax = 0 \text{ using SVD}$$

$$\text{minimize } E = \|Ax\|^2$$

$$\text{subject to } \|x\| = 1$$

$$x = \text{null}(A)$$

$$\text{SVD } A = U D V^T, \quad x = V(:, \text{end})$$

## TRIANGULATION

Given multiple  $x$ ,  $P$ s - unknown  $X$

## LINEAR TRIANGULATION

$$\begin{bmatrix} x_1 \\ 1 \end{bmatrix}_x P_1 \begin{bmatrix} X \\ 1 \end{bmatrix} = 0 \quad \text{rank}\left(\begin{bmatrix} x \\ 1 \end{bmatrix}_x P\right) = 2$$

## NONLINEAR TRIANGULATION

Rays not intersect at the same 3D point  
 Reproject the estimated 3D point to each image, consider reprojection error:  
 $(x_r, y_r) = (P_1 X^+ / P_3 X^+, P_2 X^+ / P_3 X^+)$   
 minimize  $E_r$ :

$$\min_x \sum_{i=1}^F \left( u_i - \frac{P_i^1 \tilde{X}}{P_i^3 \tilde{X}} \right)^2 + \left( v_i - \frac{P_i^2 \tilde{X}}{P_i^3 \tilde{X}} \right)^2 \quad \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} u_1 \\ v_1 \\ \vdots \\ u_F \\ v_F \end{bmatrix}$$

How to solve? - Nonlinear fitting!

## STEREO

### DEFINITION

Two cameras are in the same orientation; alignment between  $X$  axis and baseline (line between two cameras)

Epipoles at infinity

$$\frac{\text{dist}_{cam12}}{z} = \frac{\text{dist}_{x12}}{f}$$

## RECTIFICATION

**Compute  $R_{rect}$**

$$R_{rect} = \begin{bmatrix} r_x^T & r_y^T & r_z^T \end{bmatrix}^T, \quad r_x = \frac{c}{\|c\|}$$

$$r_z = \frac{\tilde{r}_z - (\tilde{r}_z \cdot r_x) r_x}{\|\tilde{r}_z - (\tilde{r}_z \cdot r_x) r_x\|}, \text{ where } \tilde{r}_z = [0 \ 0 \ 1]^T$$

$$r_y = r_z \times r_x$$

Given  $R_{rect}$ :

$$H_1 = K_1 R_{rect} K_1^{-1}, \quad H_2 = K_2 R_{rect} R^T K_2^{-1}$$

## PERSPECTIVE-N-POINTS

3D-2D correspondence

Given  $x, X$  - unknown  $P$

$$u^x = \frac{p_{11}X + p_{12}Y + p_{13}Z + p_{14}}{p_{31}X + p_{32}Y + p_{33}Z + p_{34}} \quad u^y = \frac{p_{21}X + p_{22}Y + p_{23}Z + p_{24}}{p_{31}X + p_{32}Y + p_{33}Z + p_{34}}$$

DOF is 6, at least 3 pairs of points needed

**Recover R, t from P**

$$\lambda R = K^{-1} [p_1 \quad p_2 \quad p_3] = U D V^T$$

$$R = U V^T, \text{ to make sure } \det(R) = 1$$

$$R = U \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \det(UV^T) \end{pmatrix} V^T$$

$$t = K^{-1} p_4 / d_{11}$$

**Another solution for P3P**

\* Collinear points cause ambiguity

$$\begin{cases} d_1^2 + d_2^2 - 2d_1 d_2 \cos \theta_{12} = p_{12}^2 \\ d_1^2 + d_3^2 - 2d_1 d_3 \cos \theta_{13} = p_{13}^2 \\ d_2^2 + d_3^2 - 2d_2 d_3 \cos \theta_{23} = p_{23}^2 \end{cases}, \text{ where}$$

$$p_{ij} = d(X_i, X_j), \quad \cos \theta_{ij} = \frac{(K^{-1} x_i)^T (K^{-1} x_j)}{\|K^{-1} x_i\| \|K^{-1} x_j\|}$$

Four set of possible  $(d_1, d_2, d_3)$

Use another point to verify solution.

[Recover R, t from  $(d_1, d_2, d_3)$ ]

$$[\tilde{X}_1 \quad \tilde{X}_2 \quad \tilde{X}_3] = R [X_1 \quad X_2 \quad X_3]$$

where  $\tilde{X}_i = d_i K^{-1} x_i / \|K^{-1} x_i\|$

## NON-LINEAR FITTING

$$f(x) = b$$

minimize  $E = \|f(x) - b\|^2$

$$= \text{minimize } f(x)^T f(x) - 2b^T f(x)$$

$$\frac{\partial E}{\partial x} \Big|_{x^*} = 2 \left( \frac{\partial f}{\partial x} \right)^T f(x) - 2 \left( \frac{\partial f}{\partial x} \right)^T b = 0$$

where  $J = \frac{\partial f}{\partial x}$  is the Jacobian

Use gradient descent to solve iteratively

$$f(x + \Delta x) = f(x) + \frac{\partial f}{\partial x} \Delta x, \text{ plug in:}$$

$$J^T J \Delta x = J^T (b - f(x)) \Rightarrow \Delta x = (J^T J)^{-1} J^T (b - f(x))$$

## FEATURE MATCHING

### SIFT

Repeatable, discriminative, oriented

### RANSAC

**Decide number of iterations  $N$**

$s$  - number of feature pairs in a sample

$e$  - probability that a point is an outlier

$N$  - number of iterations

$p$  - desired probability of getting good  $H$

$$1 - (1 - (1 - e)^s)^N = p$$

$$N = \log(1 - p) / \log(1 - (1 - e)^s)$$

## APPENDIX

### CROSS PRODUCT

$$a \times b = \begin{bmatrix} a_2 b_3 - a_3 b_2 \\ a_3 b_1 - a_1 b_3 \\ a_1 b_2 - a_2 b_1 \end{bmatrix} = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = [a]_x b$$