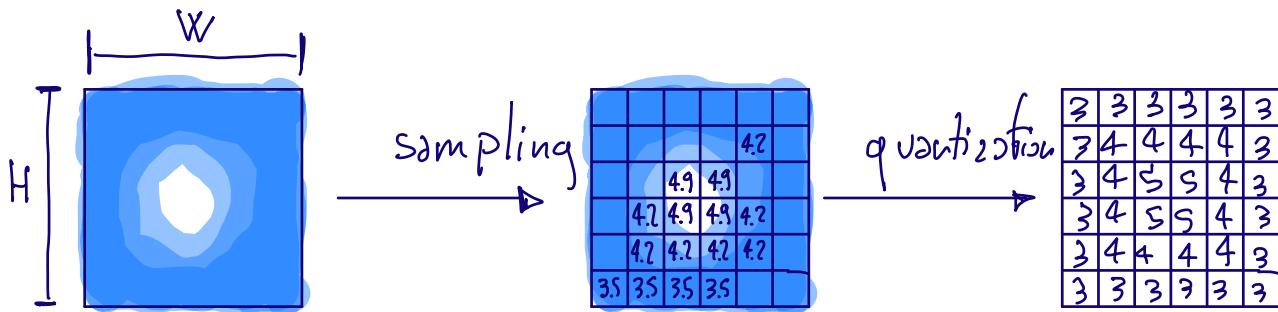


# IMAGE PROCESSING BASICS

## O SAMPLING AND QUANTIZATION



$$\Delta H = H/M$$

$$\Delta W = W/N$$

for  $i$  in  $(0, M-1)$

  for  $j$  in  $(0, N-1)$ :

$$x = (i + 0.5) \cdot \Delta H$$

$$y = (j + 0.5) \cdot \Delta W$$

$$f_{i,j} = f(x, y) \quad // \text{SAMPLING}$$

$$q_{i,j} = \lfloor L \cdot f_{i,j} \rfloor \quad // \text{QUANTIZATION}$$

$L$  intensity interval

## ② SUPERSAMPLING

- CALCULATE MEAN OF MULTIPLE POINTS IN ONE PIXEL

$$\begin{array}{|c c|} \hline \bullet & \bullet \\ \hline \bullet & \bullet \\ \hline \end{array} \quad \frac{1}{4} \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$$

- SPATIAL INTEGRATION

$$f_{i,j} = \frac{1}{\Delta W \cdot \Delta H} \int_{j \Delta W}^{(j+1) \Delta W} \int_{i \Delta H}^{(i+1) \Delta H} f(x, y) dx dy$$

## ③ SOLVE QUANTIZATION ISSUES

$$z_{i,j} = \lfloor L \cdot f_{i,j} \rfloor$$

IF Range is 0 to  $L-1$

if  $f_{i,j}$  is max, then  $f_{i,j} = L > L-1$ !

Sol 1

$$\text{round}(L \cdot f_{i,j} - 0.5) \text{ only if } r(0.5) = 0!$$

Sol 2

$\text{round}((L-1) f_{i,j})$  works but extreme bins are small

Sol 3 INCREASE DYNAMIC RANGE

$$z_{i,j} = \left\lfloor L \cdot \frac{f_{i,j} - f_*}{f^* - f_*} \right\rfloor \quad f_* = \min_{x,y} f(x,y) \quad f^* = \max_{x,y} f(x,y)$$

## ① IMAGE SIZE

Data  $M \cdot N \cdot K$  where  $L = 2^K$

Spatial 1 inch = 2.54 cm dpi

$X \cdot Y$  image @ n dpi  
 $\Leftrightarrow$

$\frac{X}{\text{dpi}}$  = size in inch width

$\frac{Y}{\text{dpi}} \cdot 2.54$  = size in cm height

## ② ZOOM IN (repetition)

in:  $A_1 M_1 \times N_1$

out:  $A_2 M_2 \times N_2$

scale factor z

so

$$M_2 = z M_1 \quad N_2 = z N_1$$

For i in  $(0, M_1 + 1)$

for j in  $(0, N_1 + 1)$

for k in  $(0, z - 1)$

for l in  $(0, z - 1)$

$$\partial_{z \cdot i + k, z \cdot j + l}^2 = \partial_{i,j}^1$$

## ③ ZOOM OUT (averaging)

in:  $A_1 M_1 \times N_1$

out:  $A_2 M_2 \times N_2$

scale factor z

so

$$M_1 = z M_2 \quad N_1 = z N_2$$

For i in  $(0, M_2 - 1)$

for j in  $(0, N_2 - 1)$

$$\partial_{i,j}^2 = 0$$

for k in  $(0, z - 1)$

for l in  $(0, z - 1)$

$$\partial_{i,j}^2 = \partial_{i,j}^2 + \partial_{z \cdot i + k, z \cdot j + l}^1$$

$$\partial_{i,j}^2 = \partial_{i,j}^2 / (z^2)$$

## Ø SCALING BY FACTOR $c$ (GENERAL SAMPLING)

in  $A_1 \quad M_1 \times N_1$

out  $A_2 \quad M_2 \times N_2$

scaling  $c$

so

$$M_2 = cM_1 \quad N_2 = cN_1$$

for i in  $(0, M_2-1)$

for j in  $(0, N_2-1)$

$$x = (i + 0.5) / c \quad // \text{continuous pixel coords}$$

$$y = (j + 0.5) / c \quad //$$

$$k = \lfloor x \rfloor \quad // \text{nearest neighbour interp}$$

$$l = \lfloor y \rfloor \quad //$$

$$\partial_{ij}^2 = \partial_{k,l}^1$$

## ~ ALTERNATIVE TO NEAREST NEIGHBOUR INTERPOL ~

### Ø BILINEAR

for i in  $(0, M_2-1)$ :

    for j in  $(0, N_2-1)$ :

$$x = (i + 0.5) / c \quad // \text{continuous pixel coords}$$

$$y = (j + 0.5) / c \quad // \text{continuous pixel coords}$$

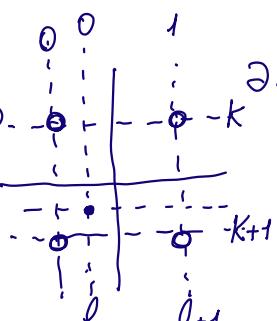
$$k = \text{round}(x) - 1$$

$$l = \text{round}(y) - 1$$

$$u = x - (k + 0.5)$$

$$v = y - (l + 0.5)$$

$$\partial_{ij}^2 = \text{round} \left( ((1-u)(1-v))\partial_{k,l}^1 + (1-u)(v)\partial_{k+1,l}^1 + (v)(1-u)\partial_{k,l+1}^1 + (v)(u)\partial_{k+1,l+1}^1 \right)$$



$$\partial_{ij}^2 = \partial_{k,l}^1 (1-u)(1-v)$$

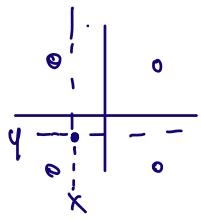
$$+ \partial_{k+1,l}^1 (u)(1-v)$$

$$+ \partial_{k,l+1}^1 (1-u)(v)$$

$$+ \partial_{k+1,l+1}^1 (u)(v)$$

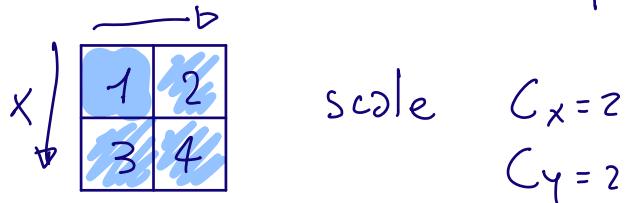
## ① BILINEAR WITH INTEGRAL

$$z_{i,j}^2 = \int_{y-0.5}^{y+0.5} \int_{x-0.5}^{x+0.5} f_1(s,t) ds dt$$

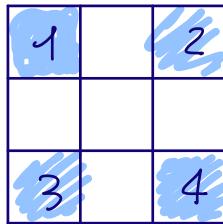


## ② GEOMETRIC TRANSFORMATIONS

- SCALING  $\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} C_x & 0 \\ 0 & C_y \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = C \begin{pmatrix} x \\ y \end{pmatrix}$



$$\begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$



$$\begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 2 \end{pmatrix}$$

$$\begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 2 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 2 \\ 2 \end{pmatrix}$$

- TRANSLATION  $\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} x + t_x \\ y + t_y \end{pmatrix}$

### - ROTATION

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = R \begin{pmatrix} x \\ y \end{pmatrix}$$

### - VERTICAL SHEAR

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} x + S_v y \\ y \end{pmatrix} = \begin{pmatrix} 1 & S_v \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = S_v \begin{pmatrix} x \\ y \end{pmatrix}$$

### - HORIZONTAL SHEAR

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} x \\ y + S_h x \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ S_h & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = S_h \begin{pmatrix} x \\ y \end{pmatrix}$$

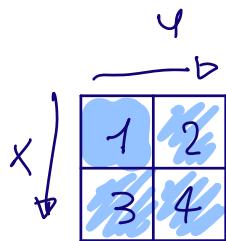
## ○ GEOMETRIC AFFINE TRANSFORMATION

From Cartesian  $\Psi: \mathbb{R}^2 \rightarrow \mathbb{R}^2$

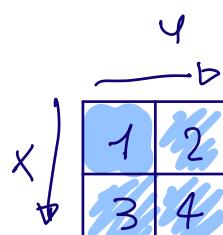
To  $\begin{pmatrix} \Psi \\ 1 \end{pmatrix}$

## - SCALING

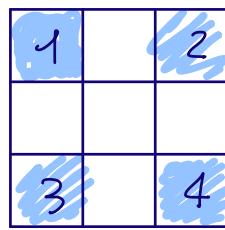
$$C(C_x, C_y) = \begin{pmatrix} C_x & 0 & 0 \\ 0 & C_y & 0 \\ 0 & 0 & 1 \end{pmatrix}$$



$$C(C_x, C_y)^{-1} = C\left(\frac{1}{C_x}, \frac{1}{C_y}\right)$$



$$C_x = C_y = 2$$



$$\begin{pmatrix} C_x & 0 & 0 \\ 0 & C_y & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 2 \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 2 \\ 0 \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 2 \\ 2 \\ 1 \end{pmatrix}$$

INVERSE

$$\begin{pmatrix} \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 2 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 2 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 2 \\ 2 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

- TRANSLATION

$$T(t_x, t_y) = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix} T(t_x, t_y)^{-1} = T(-t_x, -t_y)$$

- ROTATION

$$R(\theta) = \begin{pmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} R(\theta)^{-1} = R(-\theta)$$

- VERTICAL SHEAR

$$S_v(\lambda) = \begin{pmatrix} 1 & \lambda & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} S_v(\lambda)^{-1} = S_v(-\lambda)$$

- HORIZONTAL SHEAR

$$S_h(\lambda) = \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} S_h(\lambda)^{-1} = S_h(-\lambda)$$

## ① FORWARD MAPPING

Transform  $A_1$  int.  $A_2$  using  $A$

- For all pixels  $(x', y')$  in  $A_2$   
use  $A^{-1}$  to compute  $(x, y)$  in  $A_1$  and  
get an intensity at  $(x, y)$  using an  
interpolation method

## ② 3-SHEARS = ROTATION

$$R(\theta) = S_v(\lambda) S_h(\nu) S_v(\lambda)$$

$$\lambda = -\tan \frac{\theta}{2} \quad \nu = \sin \theta$$

for  $-\pi < \theta < \pi$

$$\text{ex: } 30^\circ \theta \quad \lambda = -0.85 \quad \nu = 0.6560$$

$$\begin{array}{c} \begin{array}{|c|c|} \hline 2 & 3 \\ \hline 4 & 1 \\ \hline \end{array} \rightarrow \left\{ \begin{array}{l} \begin{pmatrix} 1 & \lambda & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \\ \begin{pmatrix} 1 & \lambda & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \end{array} \right. \\ \left. \begin{array}{l} \begin{pmatrix} 1 & \lambda & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} \lambda \\ 1 \\ 1 \end{pmatrix} \\ \begin{pmatrix} 1 & \lambda & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \end{array} \right\} \\ \left\{ \begin{array}{l} \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \\ \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \end{array} \right. \\ \left. \begin{array}{l} \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} \\ \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \end{array} \right\} \\ \begin{array}{|c|c|} \hline 3 & \\ \hline 2 & 1 \\ \hline 4 & \\ \hline \end{array} + \text{STEP 3} \end{array}$$

$$\begin{array}{c} \begin{array}{|c|c|} \hline 3 & \\ \hline 2 & 1 \\ \hline 4 & \\ \hline \end{array} \rightarrow \left\{ \begin{array}{l} \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \\ \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \end{array} \right. \\ \left. \begin{array}{l} \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} \\ \begin{pmatrix} 1 & 0 & 0 \\ \lambda & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \end{array} \right\} \end{array}$$

## ① CHANGE INTENSITY RESOLUTION

map  $\{0, \dots, L_1 - 1\}$  to  $\{0, \dots, L_2 - 1\}$

$$r \rightarrow \text{round} \left( (r + 0.5) \frac{L_2}{L_1} - 0.5 \right)$$

(ex:

$$in = 23 \rightarrow \text{round} \left( (23 + 0.5) \frac{255}{100} - 0.5 \right) = 59$$

## ② REMOVE NOISE (TEMPORAL INTENSITY SUPERSAMPLE)

sample the source  $k$  times

$$\bar{A}_K = \frac{1}{k} \sum_{i=1}^k A_i \quad k \rightarrow \infty \text{ No noise!}$$

Recursive

$$\bar{A}_{K+1} = \frac{k \cdot \bar{A}_K + A_{K+1}}{k+1}$$

if uncorrelated noise with zero  $N$  and  $\text{STD}$

$$\text{then } \sigma_{\bar{A}_K} = \frac{1}{\sqrt{k}} \sigma_\eta$$

## ○ INTENSITY TRANSFORMATIONS

$f: I \rightarrow I$  usually bijective

injectivity: all intensity in  $f$  is used

surjectivity: all intensity in  $g$  is used

- DISCRETE SETTING

$$\hat{T}: \{0, \dots, L-1\} \rightarrow \{0, \dots, L-1\}$$

$$\hat{T}(r) = \text{round} \left( L \cdot T \left( \frac{r + 0.5}{L} \right) - 0.5 \right)$$

## ○ NEGATIVE

$$T(r) = 1 - r \quad \hat{T}(r) = L - 1 - r$$

## ○ LOG TRANSFORM

enhance contrast in dark regions

$$T(r) = 2 \log \left( r / \beta + 1 \right)$$

$\alpha = 1 / (\log(1/\beta + 1))$   
 $\beta = 1 / (\exp(1/\alpha) - 1)$

## ○ EXP TRANSFORM

enhance contrast in bright region

$$T(r) = \beta \left( \exp\left(\frac{r}{\alpha}\right) - 1 \right) \quad \begin{aligned} \alpha &= 1 / (\log(1/\beta + 1)) \\ b &= 1 / (\exp(1/\alpha) - 1) \end{aligned}$$

## ○ GAMMA CORRECTION

$$T(r) = r^\gamma \quad \gamma > 0$$

if  $\gamma < 1$  enhance contrast in dark

if  $\gamma > 1$  enhance contrast in light

## ○ CONTRAST STRETCHING

Medium intensity contrast enhance

$$T(r) = \frac{1}{2} \left( \underbrace{\arctan(\delta(2r-1))}_{\arctan(\delta)} + 1 \right) \quad \delta > 0$$

or

$$T(r) = \frac{1}{2} \left( \lambda \underbrace{\arctan(\delta(2r-1))}_{\arctan(\delta)} + 1 \right) \quad \delta > 0 \quad \lambda \geq 1$$

## ○ THREE PIECES

$$S_1 = 0$$

$$S_2 = 1$$

$f(r) = \text{piecewise, bijective, linear function}$

$r_1 = \text{fresh 1}$

$r_2 = \text{fresh 2}$

## ○ INTENSITY LEVEL SLICING

highlight one area

## ○ NORMALIZE HISTOGRAM

$$P_K = \frac{h_k}{M \cdot N} \quad \sum_{K=0}^{L-1} P_K = 1$$

## ○ HISTOGRAM EQUALIZATION

Make histogram as uniform as possible

continuous setting  $p(r) \geq 0$  probability density funct

$$\text{with } \int_0^1 p(r) dr = 1$$

at a position  $(x, y)$ ,  $f(x, y)$

has to be between  $r_1$  and  $r_2$

and is  $\int_{r_1}^{r_2} P(r) dr$

$$q(s) = \frac{P(r)}{\bar{T}(r)}$$
$$q(s) = \frac{1}{\bar{T}(r)} \int_{r_1}^r P(r) dr = P(r)$$

digital setting

$$P(r/L) = L \cdot P_K \quad \text{for } r \in [k, k+1]$$

then  $\bar{T}(k/L) = \sum_{j=0}^{K-1} P_j$

for  $K = 0, \dots, L$

FORMULA :  $\hat{T}(k) = \text{round}(\tilde{s}_k)$

$$\tilde{s}_k = L \sum_{j=0}^{K-1} P_j + \frac{L}{2} P_K - \frac{1}{2}$$

$k = 0, \dots, L-1$

## ① HISTOGRAM MATCHING

$$T = T_q^{-1} \circ T_p \quad T_p(k/l) = \sum_{j=0}^{k-1} p_j$$

$$T_q^{-1} = \frac{k}{l}$$

## ② LINEAR SPATIAL FILTERING

- box  $\sigma = b$ ,  $m=n=2\sigma+1$ ,  $w_{s,t} = \frac{1}{m^2}$

- gaussian  $\sigma = b$

$$w_{s,t} = \frac{\exp\left(-\frac{s^2+t^2}{2\sigma^2}\right)}{-\partial\left(\exp\left(-\frac{s^2+t^2}{2\sigma^2}\right)\right)}$$

## ③ PADDING

- zero
- mirror
- replicate

## ④ PERFORMANCE

$$\mathcal{O}(MNmn)$$

can be improved with separable kernel

① MEDIAN FILTER (KERNEL)

Median value of Kernel window

② LAPLACIAN (BIVARIATE)

$$L = l \star A$$

$$l = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$l^1 = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

③ PREWITT (KERNEL) (Box Smoothing)

$$g_x = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$g_y = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

gradient magnitude

$$\sqrt{(g_x \star A)^2 + (g_y \star A)^2}$$

## ① SOBEL (Gaussian smoothing)

$$g_x = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad g_y = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

gradient magnitude

$$\sqrt{(g_x * A)^2 + (g_y * A)^2}$$

## ② BASIC BINARIZE

$$\begin{cases} 0 & \text{if } A_{ij} \leq t \\ 1 & \text{else} \end{cases}$$

Threshold selection

- Fit poly or Fit gauss. dists

## ③ IMAGE SEGMENTATION

$$\bigcup_{i=1}^n R_i = R$$

$R_i$  connected set  $i=0, \dots, n$

$R_i \cap R_j = \emptyset$  for all  $i, j$

If some value but different regions  $\Rightarrow$  different sets

O SIGNAL SMOOTHING (square Kernel) O AVG SMOOTHING ( $n \cdot m$  Kernel)

$h = \text{kernel size}$

$$g_i = \frac{1}{h} \int_{i-h/2}^{i+h/2} f(x) dx$$

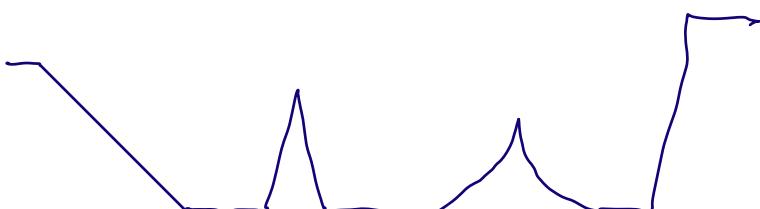
$$B_{ij} = \frac{1}{n \cdot m} \int_{i-h/2}^{i+h/2} \int_{j-m/2}^{j+m/2} A(s, t) dt ds$$

$$(B_{ij}) = \sum_{s=-h/2}^{h/2} \sum_{t=-m/2}^{m/2} A_{ij} w(i+s, j+t)$$

where

$$w = \begin{bmatrix} \frac{1}{n \cdot m} & \dots & \frac{1}{n \cdot m} \\ \vdots & \ddots & \vdots \\ \frac{1}{n \cdot m} & \dots & \frac{1}{n \cdot m} \end{bmatrix}$$

O USE 1<sup>ST</sup> DERIVATIVE TO DETECT regions



Der: 0 -1 -1 -1 0 0 4 -1 0 0 0 -1 -2 2 1 0 0 7 0 0

Ramp Isolated point Line Step

## O CANNY EDGE DETECTION

1) Integration to smooth img

2) Differentiation to compute

$$G = \sqrt{G_x^2 + G_y^2} \quad \theta = \arctan \frac{G_y}{G_x}$$

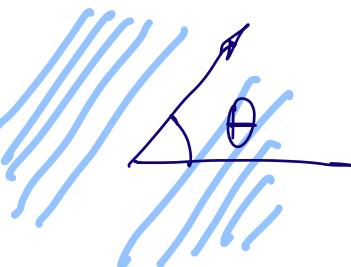
$$G_x = W_x * A \quad W_x = \begin{bmatrix} -1/2 & 0 & 1/2 \\ \end{bmatrix}$$

$$G_y = W_y * A \quad W_y = \begin{bmatrix} 1/2 \\ 0 \\ -1/2 \end{bmatrix}$$

3) Non maxima suppression

- Group angles

$$\theta_{ij}^l = \begin{cases} 0 & -22.5^\circ < \theta < 22.5^\circ \\ 45 & 22.5^\circ \leq \theta < 67.5^\circ \\ 90 & 67.5^\circ \leq \theta < 142.5^\circ \\ 135 & 142.5^\circ \leq \theta < 157.5^\circ \end{cases}$$



$G_{i-1,j}$
$G_{i,j}$
$G_{i+1,j}$

4) Magnitude comparison

if  $\theta_{ij}^l = \theta$

if  $6_{ij} < 6_{(i-1)j}$  or  $6_{ij} < 6_{(i+1)j}$ :

$$G_{ij}^l = 0$$

if  $\theta_{ij}^l = 45$

if  $6_{ij} < 6_{(i-1)(j+1)}$  or  $6_{(i+1)(j-1)} < 6_{ij}$ :

$$G_{ij}^l = 0$$

if  $\theta_{ij}^l = 90$

if  $6_{ij} < 6_{(i-1)j}$  or  $6_{ij} < 6_{(i+1)j}$ :

$$G_{ij}^l = 0$$

if  $\theta_{ij}^l = 135$

if  $6_{ij} < 6_{(i-1)j}$  or  $6_{ij} < 6_{(i+1)j}$ :

$$G_{ij}^l = 0$$

else

$$G_{ij}^l = 6_{ij}$$

## 2) Hysteresis thresholding

choose 2 thresholds

and form an image with

points of intensity  $> t_h$

and 1 other image of points  
of intensity  $< t_l$

label points as  
2 if  $G_{ij} \geq th$   
1 if  $t_h \leq G_{ij} \leq th$

0 if  $G_{ij} \leq t_l$

### - Connectivity analysis

Using result of Hysteresis

1) choose a point in class 2

2) and recursively grow seed to  
include neighbours with magnitude  
 $\geq 1$

3) Repeat 1 and 2 until all values  
in class 2 are included

## O HARRIS-STEVENS CORNER DETECTOR

- Sum of square differences

$$C(x, y) = \sum_{s=-n/2}^{n/2} \sum_{t=-m/2}^{m/2} [A(s+x, t+y) - A(s, t)]^2$$

1 0  
 or  
 0 1

- weighted sum of square differences

$$C(x, y) = \sum_{s=-n/2}^{n/2} \sum_{t=-m/2}^{m/2} w(s, t) [A(s+x, t+y) - A(s, t)]^2$$

Smoothing  
kernel

- bilinear approximation

$$A(s+x, t+y) \approx A(s, t) + x G_x(s, t) + y G_y(s, t)$$

$$G_x = A \star \begin{bmatrix} -0.5 \\ 0 \\ 0.5 \end{bmatrix} \quad G_y = A \star \begin{bmatrix} -0.5 & 0 & 0.5 \end{bmatrix}$$

$$C(x, y) = \sum_{s=-n/2}^{n/2} \sum_{t=-m/2}^{m/2} w(s, t) [A(s+x, t+y) - A(s, t)]^2$$

Smoothing  
kernel

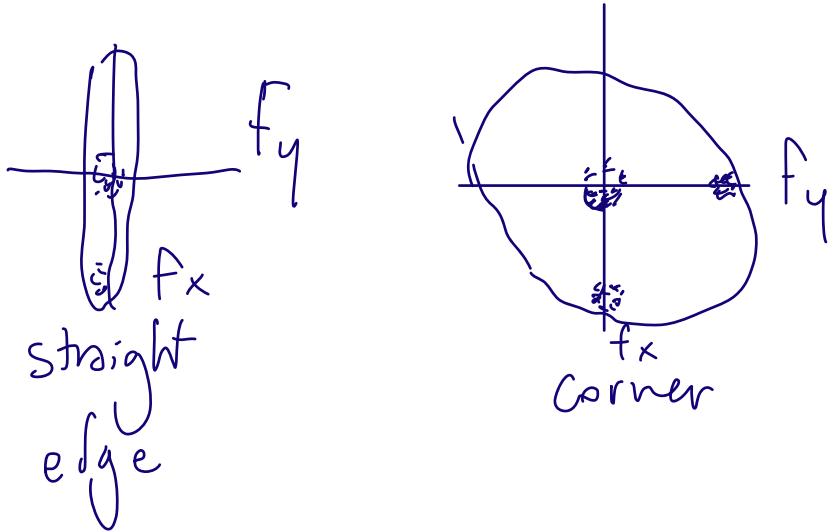
norm value / max

$$C(x,y) = [x \ y] M \begin{bmatrix} x \\ y \end{bmatrix}$$

$$M = \sum_s \sum_t w(s,t) \begin{bmatrix} G_x(s,t)^2 & G_x(s,t)G_y(s,t) \\ G_x(s,t)G_y(s,t) & G_y(s,t)^2 \end{bmatrix}$$

covariance matrix representing  
the form  $(A_x^2 + B_{xy} + C_y^2)$

So if we compute eigenvectors  
of Harris matrix, we get:



We can summarize eigenvalue computation by:

$$R = \lambda_x \lambda_y - k (\lambda_x + \lambda_y)^2 = \det(M) - k \text{trace}^2(M)$$

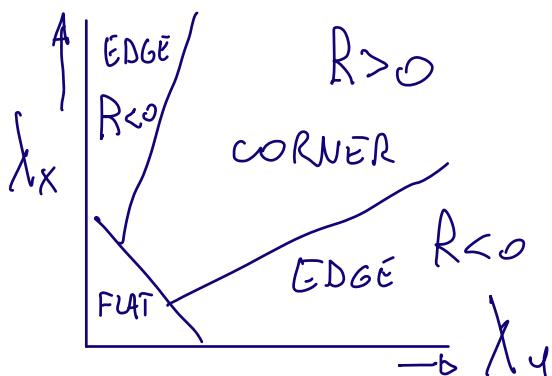
$$\det(M) = G_x(s, t)^2 G_y(s, t)^2 - [G_x(s, t) G_y(s, t)]^2$$

$\uparrow$   
 $= \lambda_x \lambda_y$

$$\text{trace}(M) = G_x(s, t)^2 + G_y(s, t)^2 = \lambda_x + \lambda_y$$

$$G_x = A \star \begin{bmatrix} -0.5 \\ 0 \\ 0.5 \end{bmatrix} \quad G_y = A \star \begin{bmatrix} -0.5 & 0 & 0.5 \end{bmatrix}$$

④ READ RESULTS:



## ① LIGHT TYPES:

monochrome : 1 wavelength

achromatic : all wavelength  $\approx$  equal

chromatic : all spectrum with dominant length

## ② XYZ COLOR SPACE

$$X = \frac{\int \bar{x}(\lambda) I(\lambda) d\lambda}{\int \bar{Y}(\lambda) I(\lambda) d\lambda} \quad L_{cone} = X$$
$$Y = \frac{\int \bar{Y}(\lambda) I(\lambda) d\lambda}{\int \bar{Z}(\lambda) I(\lambda) d\lambda} \quad M_{cone} = Y$$
$$Z = \frac{\int \bar{Z}(\lambda) I(\lambda) d\lambda}{\int \bar{Z}(\lambda) I(\lambda) d\lambda} \quad S_{cone} = Z$$

[ SPD of light ]

## ③ XY COLOR SPACE

$$X = \frac{X}{X+Y+Z} \quad Y = \frac{Y}{X+Y+Z} \quad Z = \frac{Z}{X+Y+Z} = 1-X-Y$$

So we use

$x, y$  and  $\Phi \rightarrow$  luminance

O RGB

CONVERSION TO XYZ

$$R: \{0, \dots, 255\}$$

$$G: \{0, \dots, 255\}$$

$$B: \{0, \dots, 255\}$$

$$\begin{pmatrix} R \\ G \\ B \end{pmatrix} = \begin{pmatrix} 3.06 & -1.39 & -0.48 \\ -0.97 & 1.88 & 0.04 \\ 0.07 & -0.23 & 1.07 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$$

O RGB  $\hookrightarrow$  CMY

$$\begin{pmatrix} C \\ M \\ Y \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} - \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

$$\begin{pmatrix} R \\ G \\ B \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} - \begin{pmatrix} C \\ M \\ Y \end{pmatrix}$$

O CMY  $\rightarrow$  CMYK

$$(CMY) = \frac{(C-k, M-k, Y-k)}{(1-k)}$$

① RGB TO HSI

H hue	0, 360
S saturat	0, 1
I intens	0, 1

$$H = \begin{cases} \theta & \text{if } B \leq G \\ 360 - \theta & \text{if } B > G \end{cases}$$

$$\theta = \arccos \left( \frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2 + (R-G)(G-B)}} \right)$$

$$S = 1 - \frac{3 \min(R, G, B)}{R + G + B} = 1 - \frac{\min(R, G, B)}{I}$$

$$I = \frac{R + G + B}{3}$$

② HSI TO RGB

$$\text{if } H \in [0, 120)$$

$$B = I(1-s)$$

$$R = I \left( 1 - \frac{s \cos H}{\cos(60-H)} \right)$$

$$G = 3I - (R+B)$$

$$\text{elif } H \in [120, 240]$$

$$H = H - 120$$

$$R = I(1-s)$$

$$G = I \left( 1 - \frac{s \cos H}{\cos(60-H)} \right)$$

$$B = 3I - (R+G)$$

$$\text{elif } H \in [240, 360)$$

$$H = H - 240$$

$$G = I(1-s)$$

$$B = I \left( 1 - \frac{s \cos 60}{\cos(60-H)} \right)$$

$$R = 3I - (G+B)$$

## ② PSEUDO COLORS

$$f: X \times Y \rightarrow I$$

Input

$$T_R, T_G, T_B : I \rightarrow I$$

output

$$g_R, g_G, g_B : X \times Y \rightarrow I \quad \text{where } g_\star(x, y) = T_\star(F(x, y))$$

## ③ CARTESIAN

$$(x, y)$$

## ④ BARYCENTRIC

$$\cdot(1, 0, 0)$$

$$\cdot(0, 1, 0)$$

$$\cdot(0, 2s, -0, 2s, +)$$

$$\cdot(0, 0, 1)$$

## ⑤ ADD ELEMENTS IN Ph

$$\begin{pmatrix} x \\ v \end{pmatrix} \oplus \begin{pmatrix} y \\ w \end{pmatrix} = \begin{pmatrix} vx \\ ov \end{pmatrix} \begin{pmatrix} u \\ w \end{pmatrix} = \begin{pmatrix} vu + wv \\ vw \end{pmatrix}$$

## ⑥ EUCLIDEAN

using cartesian

2 points  $\Rightarrow$  line

2 lines are parallel  $\Leftrightarrow$  never touch

## ⑦ PROJECTIVE

hom. coords

2 points  $\rightarrow$  line

2 lines are parallel  $\Leftrightarrow$  touch

① MULTIPLY ELEMENT IN  $P^4$

$$\begin{pmatrix} x \\ y \\ v \end{pmatrix} \odot \begin{pmatrix} y \\ w \end{pmatrix} = \begin{pmatrix} x & 0 \\ 0 & v \end{pmatrix} \begin{pmatrix} y \\ w \end{pmatrix}$$

$$= \begin{pmatrix} xy \\ vw \end{pmatrix}$$

## CONICS

IMPLICIT FORM :  $(x, y)^T \in \mathbb{R}^2 : ax^2 + bxy + cy^2 + dx + ey + f = 0$

DISCRIMINANT :  $S = -4\Delta$  where  $\Delta = \det M$

where  $M = \begin{pmatrix} a & b/2 \\ b/2 & c \end{pmatrix}$

non-degenerate :  $(a, b, c) \neq (0, 0, 0)$

Parabola  $S = 0$

Ellipse  $S < 0$

Circle  $(a=c, b=0) \nmid S < 0$

Hyperbola  $S > 0$

Rectangular hyperb  $S > 0 \nmid a+c=0$

○ Point on conic with homo

if point =  $(x, y, z)^T$  on conic

then

$$ax^2 + bxy + cy^2 + dxz + eyz + fz^2 = 0$$

other form

$$x^T C x = 0 \quad C = \begin{pmatrix} a & b/2 & d/2 \\ b/2 & c & e/2 \\ d/2 & e/2 & f \end{pmatrix}$$

○ CONIC THEORY

Conic is uniquely defined by

5 points  $\mathbf{x}_i = (x_i, y_i, z_i)$  for  $i=1, \dots, 5$

each point places 2 constraint on the coefficient

$$(x_i^2, x_i y_i, y_i^2, x_i z_i, y_i z_i, z_i^2) C = 0 \quad c = (a, b, c, d, e)^T$$

IF 3 OF THESE  $\mathbf{x}_i$  are collinear then not unique  $\rightarrow$  DEGENERATE

## ① DEGENERATE (Not unique conic)

- $\delta = 0 \rightarrow$  two parallel lines  
(degenerate parabola)
  - $\delta = 0 \notin (d^2 + e^2 = 4(\lambda + c)f) \rightarrow$  one (double line)
  - $\delta < 0 \rightarrow$  single point (degenerate ellipse)
  - $\delta > 0 \rightarrow$  2 intersecting lines
- ② if  $\det \neq 0, \delta < 0$  and  $(\lambda + c)\det > 0$   
then imaginary ellipse  $\Rightarrow$  empty in  $\mathbb{R}^2$

## ③ TANGENT LINE

$\ell = Cx$  is line  $\ell$  tangent to  $C$  at  $x$

IF all  $\ell$  is in  $C$ :

$\ell \in C$ ,  $C$  must be degenerate

## DUAL CONIC

All lines tangent to  $C$

So adjoint of conic  $C$ ...

$$M \cdot \text{adj}(M) = \det(M) I$$

where  $M = (M^*)^T$  where  $M^*$  is the cofactor matrix

$$\text{adj}(M) = \det(M) I \cdot M^{-1} \text{ if } M \text{ invertible}$$

$$\text{adj}(C) = C^* = C^{-1}$$

IF FULL RANK

$l$  is tangent of  $C$  and element of  $C^*$

$$\Leftrightarrow l^T C^* l = 0$$

## ○ PROJECTIVE TRANSFORMATION

$$\mathbb{P}^2 \Rightarrow \mathbb{P}^2$$

$$h(x) = Hx \quad \text{where } H \text{ is a non-singular matrix}$$

$H$  is homogenous : so it can be scaled by any  $\lambda \neq 0$

## ○ DEGREES OF FREEDOM

$H \in \mathbb{R}^{3 \times 3}$  has 8 degrees freedom

use 4 points in original and 4 in projected

~ No 3 COLLINEAR ~

## ○ TRANSFORMATION EXAMPLES

$$x \rightarrow x' = Hx$$

$$\ell \rightarrow \ell' = H^{-T} \ell$$

$$C \rightarrow C' = H^{-T} CH^{-1}$$

$$C^* \rightarrow C^{*'} = HC^*H^T$$

## ○ ISOMETRY

$$H_I = \begin{pmatrix} \epsilon \cos \theta & -\sin \theta & t_x \\ \epsilon \sin \theta & \cos \theta & t_y \\ 0 & 0 & 1 \end{pmatrix} \quad \epsilon = \pm 1$$

-  $\epsilon = 1 \rightarrow$  orientation-preserving

$\epsilon = -1 \rightarrow$  orientation-reversing (reflection)

3 degrees of freedom +  $\epsilon$

INVARIANT AREA, DISTANCES!

## ① EUCLIDEAN TRANSFORMATION

$$H_E = \begin{pmatrix} R_\theta & t \\ 0^T & 1 \end{pmatrix} \quad R_\theta = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}$$

## ② SIMILARITIES

$$H_S = \begin{pmatrix} \epsilon \cos\theta & -\epsilon \sin\theta & t_x \\ \epsilon \sin\theta & \epsilon \cos\theta & t_y \\ 0 & 0 & 1 \end{pmatrix} \quad \epsilon = \pm 1$$

4 degrees + E

invariant angles

ratios of lengths

## ① AFFINE TRANSFORMATIONS

$$H_A = \begin{pmatrix} \alpha_{11} & \alpha_{12} & f_x \\ \alpha_{21} & \alpha_{22} & f_y \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} A & \mathbf{f} \\ \mathbf{0}^T & 1 \end{pmatrix}$$

where  $A = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}$  is non-singular

6 degrees of freedom

Preserve lines & parallelism

## ② PROJECTIVE TRANSFORMATION

$$H_P = \begin{pmatrix} A & \mathbf{f} \\ \mathbf{v}^T & w \end{pmatrix}$$

$$\mathbf{v}^T = (v_1, v_2) \quad \text{and} \quad \det H_P \neq 0$$

8 deg of freedom

## ① CAMERA GEOMETRY

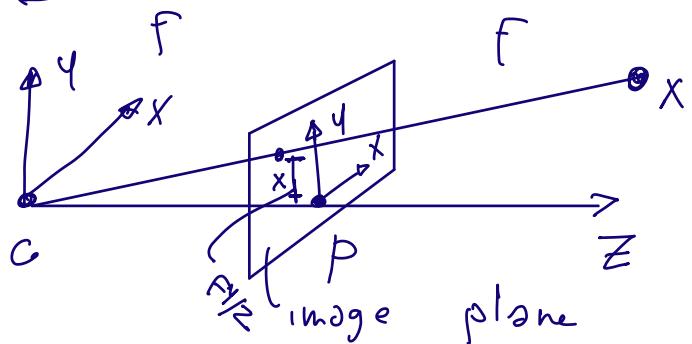
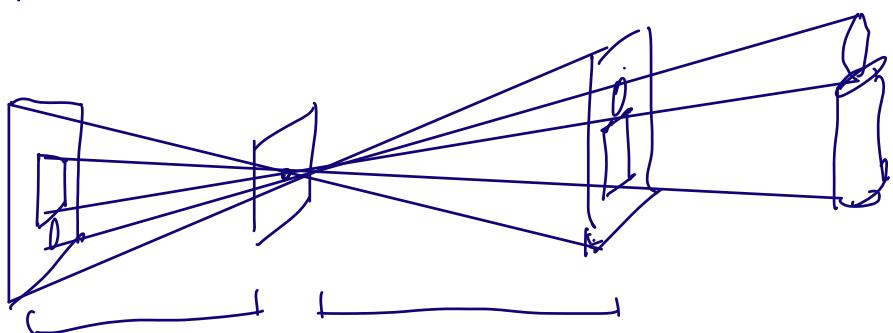
Map  $\rightarrow$  world point  $\mathbb{R}^3$  to  $\rightarrow$  image point  $\mathbb{R}^2$

- Projective transformation, represented by  
 $P \in \mathbb{R}^{3 \times 4}$  matrix

- 11 DOF!

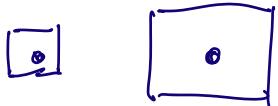
INTERNAL CAMERA PARAMS,  $K \in \mathbb{R}^{3 \times 3}$   
EXTERNAL: position  $\vec{e}$ , orientation

## OPENHOLE CAM



map world  
point  
 $(x, y, z)^T$   
into  
image plane

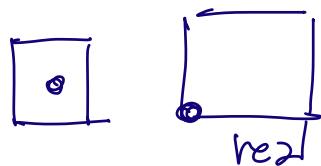
MAPPING:  $X \mapsto X = PX$   $(f_x, f_y, f)^T$  in  $\mathbb{R}^2$  img  
 $\vdash (x, y, z, 1)^T$  in  $\mathbb{R}^3$  world

- ① CENTRAL PROJECTION (PINHOLE)
  $P = \text{diag}(f, f, 1) [I | 0] = \begin{pmatrix} f & 0 \\ f & 0 \\ 1 & 0 \end{pmatrix}$ 


central projection  
with focal length  $f$

- ② OFFSET PROJECTION (PINHOLE)

$$P = K [I | 0], K = \begin{pmatrix} f & p_x \\ f & p_y \\ 1 & \end{pmatrix}$$



## ① OFFSET , DIFFERENT ORIENTATION PINHOLE

$$X = \begin{pmatrix} R & -RC \\ O^T & 1 \end{pmatrix} \tilde{X}$$

R: Rotation matrix (Orientation)  
 \$z\$ world coordinate  
 of camera center  
 world point  
 camera point

$$R = (\tilde{x}, \tilde{y}, \tilde{z})^T$$

$$X = P \tilde{X}$$

$$P = K \cdot R [I | -\tilde{c}]$$

$$= K [R | +]$$

\$-RC\$  
 Skew

$$K = \begin{pmatrix} \alpha_x & s & x_0 \\ 0 & \alpha_y & y_0 \\ 0 & 0 & 1 \end{pmatrix}$$

$\alpha_x = f \cdot m_x$   
 $\alpha_y = f \cdot m_y$   
 $x_0 = M_x \cdot p_x$   
 $y_0 = M_y \cdot p_y$   
 \$M\_x, M\_y\$ pixel size

$$P = \begin{bmatrix} M & P_4 \end{bmatrix}$$

$$M = KR \quad RQ \text{ decomp} \Rightarrow QR \text{ of } M^T \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} = QR$$

Once we have  $Q \not\in R$

$$K = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} R^T \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} \quad R = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} Q^T$$

$$P_4 = -MC$$

## OCALIBRATION

$P$  has 11 deg freedom so  
we need 5.5 points  $(x_i, y_i)_{i=1}^{12}$

Use  $x_i$  world  $\{x_i$  image  $\}$  Find  $P$  such that  $x_i = Px_i$

## ② DLT

12

$$2n \begin{bmatrix} 0, 0, 0, -x_1, -y_1, -z_1, -1, y_1, x_1, y_1, y_1, y_1, z_1, -1, y_1 \\ x_1, y_1, z_1, 1, 0, 0, 0, 0, -x_1, x_1, -x_1, y_1, -x_1, z_1, -x_1, -x_1 \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

For each point

# ① PATTERN RECOGNITION

## ~ MINIMUM-DISTANCE CLASSIFIER

$$m_j = \frac{1}{n_j} \sum_{x \in C_j} x \quad j = 1, 2, \dots, N_C$$

*class  $j$*

*/  
n° classes*

*Prototype vector for class  $j$ .*

Measure euclidian distance between  
a pattern vector and the prototype  
of each class, the pattern  
will be in the lowest euclidian  
distance class

$$\underset{j \in 1 \dots N_C}{\operatorname{argmin}} \|x - m_j\|$$

## ① TEMPLATE MATCHING

$$(w \star f)(x, y) = \sum_s \sum_t w(s, t) f(x+s, y+t)$$

examples of CROSS CORRELATION

⑥

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \star \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 9 & 8 & 7 & 0 \\ 0 & 6 & 5 & 4 & 0 \\ 0 & 3 & 2 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$f$

⑦

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 2 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \star \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 3 & 2 & 1 \\ 2 & 6 & 8 & 6 & 2 \\ 3 & 8 & 12 & 8 & 3 \\ 2 & 6 & 8 & 6 & 2 \\ 1 & 2 & 3 & 2 & 1 \end{bmatrix}$$

$f$

## Example of convolution

$$\textcircled{2} \quad \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 2 & 3 & 0 \\ 0 & 4 & 5 & 6 & 0 \\ 0 & 7 & 8 & 9 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$\downarrow$

$f \qquad w$

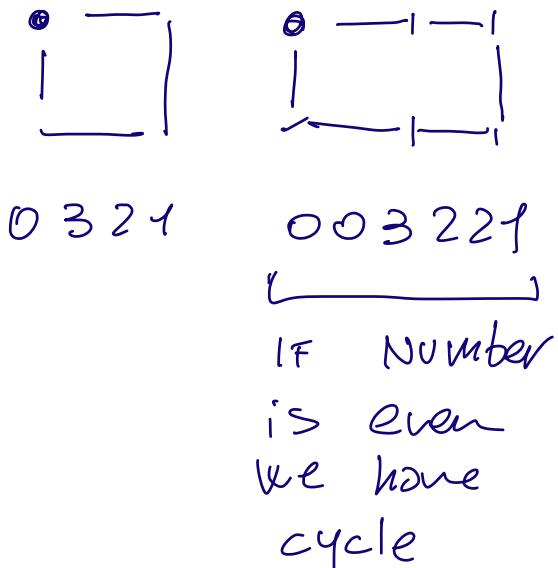
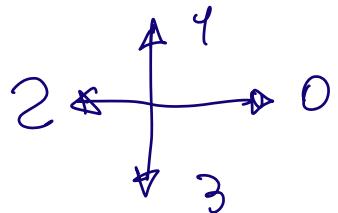
$$\begin{bmatrix} 9 & 8 & 7 \\ 6 & 5 & 4 \\ 3 & 2 & 1 \end{bmatrix} \quad \text{same thing}$$

## o Correlation coefficient

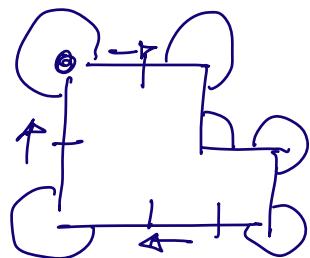
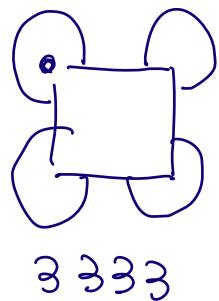
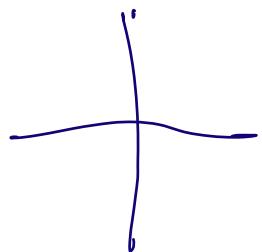
Get mean of window and subtract it out of each value!

## ① MATCHING STRUCTURAL PATTERNS

### - Shape numbers



### - Shape numbers (rotation invariant)

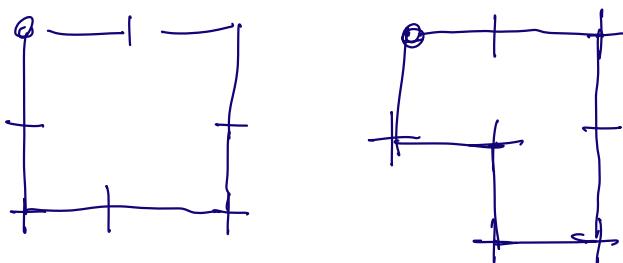


3 0 3 1 3 3 0 0 3 0  
even

- shift by  $n^o$  of possible directions to get smallest number

We compare 2 images,  
2 vals at 2 time.

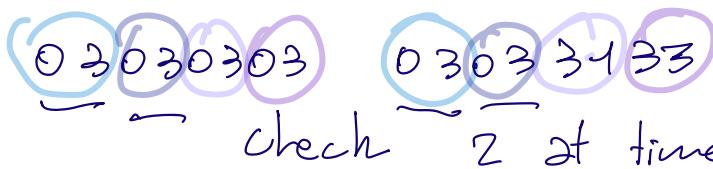
ex:



30303030      30303313

shift by 4 dirs

GET THE BEST:

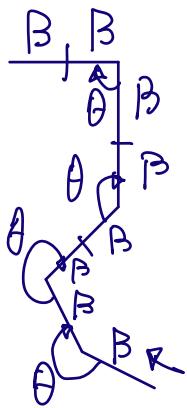
 check 2 at time 0000

here 4 are same so  $K=4$

$$D(a, b) = \frac{1}{K} \text{ Distance}$$

\sum\_{s \in S}

AS STRINGS...



$$\sigma = B \theta B \theta B B \theta B B \theta B B$$

count number of matches  
between  $\sigma$  &  $b$

$$B = \left( \begin{array}{l} \text{max length} \\ \text{between the} \\ 2 \text{ strings} \end{array} - h^o \text{ matches} \right)$$

$$r = \frac{h^o \text{ matches}}{B}$$

Matching  
can be done  
with edit distances

# ① HOG Histogram oriented gradients

1 -  $64 \times 128$  DETECTION WINDOW

2 - DIVIDE THE WINDOW INTO  $6 \times 6$  PIXELS CELLS

3 - COMPUTE QUANTIZED GRADIENT ORIENTATION

$$\theta = \arctan\left(\frac{G_y}{G_x}\right)$$

4 - GROUP  $3 \times 3$  CELLS INTO BLOCKS

5 - NORMALIZE GRADIENT MAGNITUDES BY CELL BLOCKS

6 - TRUNCATE NORMALIZED CELL RESPONSES

7 - TRAIN CLASSIFIER

---

1)  $n \times m$  window

2) Divide in  $6 \times 6$  cells

3) Group cells in  $3 \times 3$  blocks

4) COMPUTE

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \quad G_y = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

gradient  $G = \sqrt{G_x^2 + G_y^2}$   
 magnitude

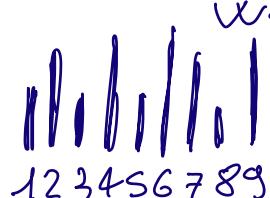
orientation:  $\theta = \arctan \frac{G_y}{G_x}$

## BIN ORIENTATIONS AS

- 1  $0 < 20$
- 2  $20 < 40$
- 3  $40 < 60$
- 4  $60 < 80$
- 5  $80 < 100$
- 6  $100 < 120$
- 7  $120 < 140$
- 8  $140 < 160$
- 9  $160 < 180$

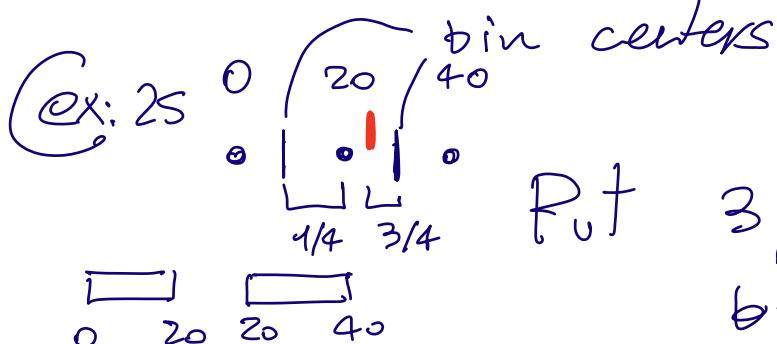
USE THIS TO CREATE  
 AN HISTOGRAM FOR EACH  
 CELL

→ each pixel is  
 weighted by  
 $G$ :



gradient  
 magnitude

## ALTERNATIVE TO BINNING:



Put  $3/4^{th}$  on the 20-40  
 bin and  $1/4^{th}$   
 in the other

4) THEN GROUP EACH CELL INTO BLOCK

5) Normalize gradient magnitudes  
by cell blocks

For a block:

$$V = \frac{v}{\sqrt{N\|v\|_2^2 + \epsilon^2}}$$

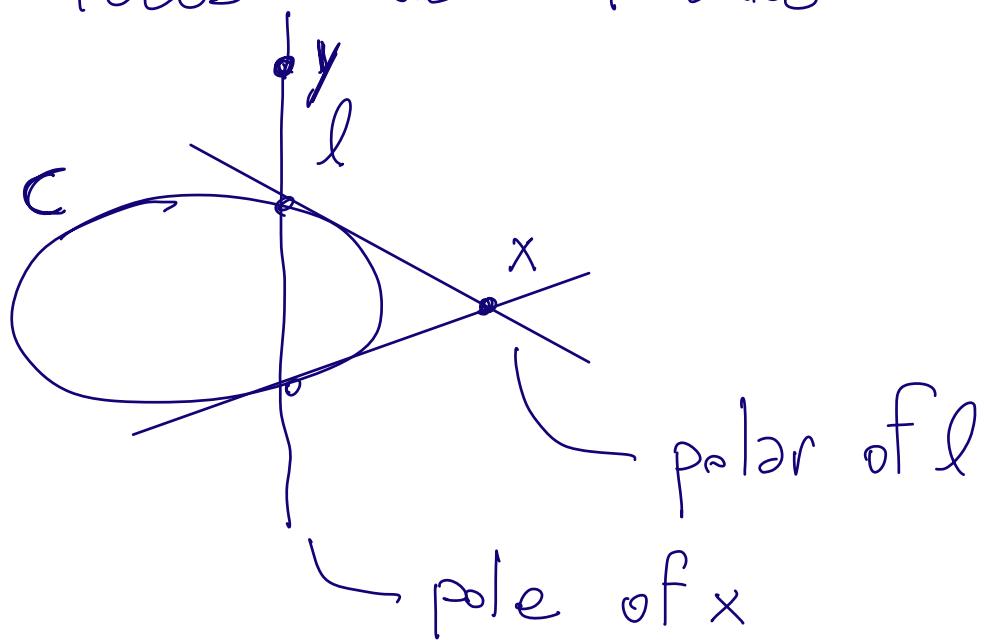
un-normalized vector  
of all 9 histograms  
in a block

$\epsilon$  constant to  
avoid  $\frac{x}{0}$

6) Truncate normalized vector  
~FLATTEN~

7) TRAIN WITH SOFT MARGIN SVM

## ① POLES AND POLARS



$x, y$  conjugate if  $x^T C y = y^T C x = 0$

,  $x$  and any  $y$  on the polar of  $x$  are conjugate

- If  $y$  is on the polar of  $x$  then  $x$  is on the polar of  $y$
- two lines  $l, m$  are conjugate, if

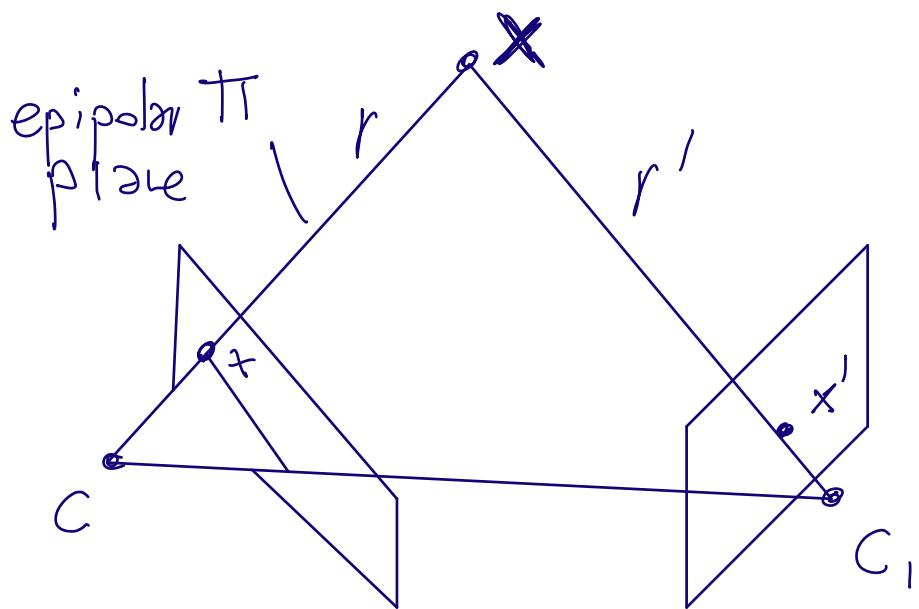
$$l^T C^* m = m^T C^* l$$

## ② STEREO VISION

2 Projection matrices

given  $x$  in first image

where is  $x'$  in second image?

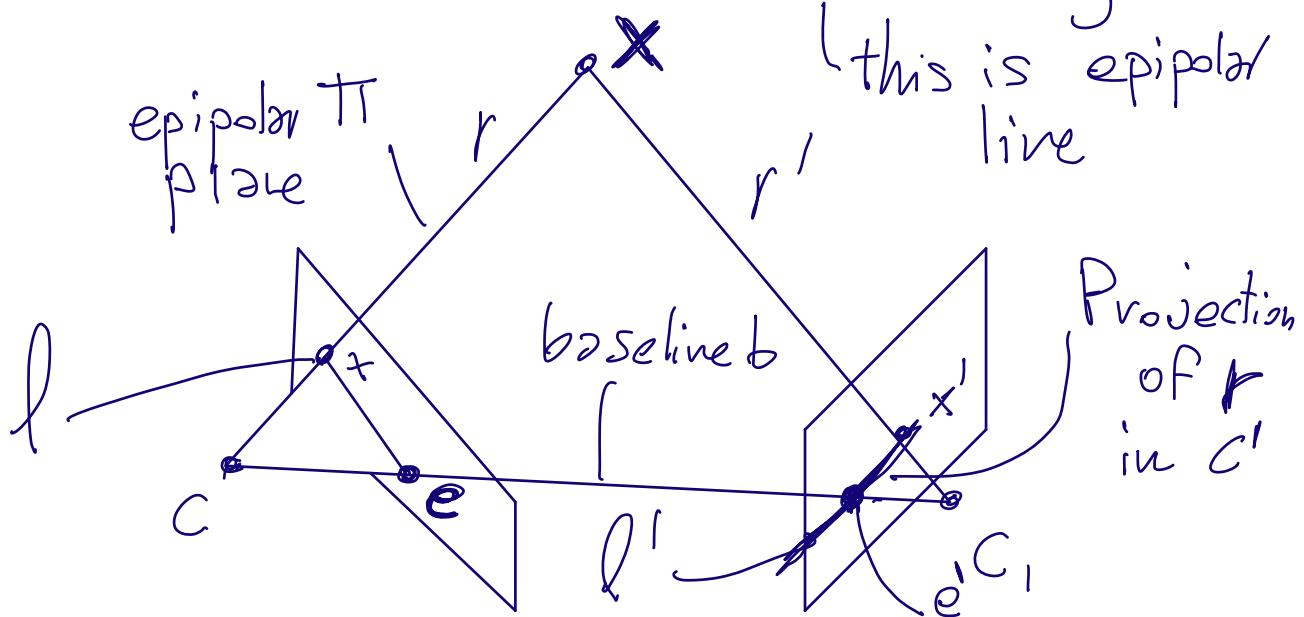


camera centers are on a common plane  $\pi$

~~X~~ projects to  $x$  and  $x'$

~~X~~,  $x$ ,  $x'$ ,  $C$ ,  $C'$  are coplanar

- Given  $x$  we know ~~X~~ must lie on  $r = \vec{C}x$
- and  $x'$  must lie on  $r' = \vec{C}'x$
- $x'$  must lie on the projection of  $r$  into the image of  $C'$



o Mapping from  $x \rightarrow l'$  from a point  
 in the first image to the corresponding  
 epipolar line in  $C'$  picture :  $l'$

THIS MAPPING IS  $l' = Fx$   
 where  $F = [e']_x P'P^+$  (Fundam. matrix)  
 $e'$   
 $C'_\text{in}$   
 $C'_\text{image}$

So we get  $e' = \begin{pmatrix} e'_1 \\ e'_2 \\ e'_3 \end{pmatrix}$

$$F = \begin{bmatrix} 0 & -e'_3 & e'_2 \\ e'_3 & 0 & -e'_1 \\ -e'_2 & e'_1 & 0 \end{bmatrix} \cdot P' \left( P^T (P P^T)^{-1} \right)$$

General case to get  $e$ :

$$P = [M | P_4] \quad P' = [M' | P'_4]$$

then

$$e = -MM'^{-1}P'_4 + P_4 \quad e' = -M'M^{-1}P_4 + P'_4$$

and

$$F = \begin{bmatrix} 0 & -e'_3 & e'_2 \\ e'_3 & 0 & -e'_1 \\ -e'_2 & e'_1 & 0 \end{bmatrix} M' M^{-1}$$

DECOMPOSE

$$F = F_S + F_d \quad F_d = (F - F^T)/2$$

$$F_S = (F + F^T)/2$$

$$l' = Fx$$

Find intersection  $x_c$  of the epipolar line through  $e$  and  $x$  with  $F_S$

