

Chapter 5

changes in brightness in an image are important

Image gradient

$$\nabla I = \begin{bmatrix} \frac{\partial I}{\partial x} \\ \frac{\partial I}{\partial y} \end{bmatrix}$$

$[dx, dy] = \text{gradient (im)}$; $\text{dir} = \text{atan2}(dy, dx)$;
 $\text{mag} = \text{sqrt}(dx^2 + dy^2)$; $\text{ori} = \text{atan2}(dy, dx)$

Derivative of Gaussian filters

can convolve derivative of Gaussian with image rather than smoothing derivative of image

$$\frac{\partial (G \otimes I)}{\partial x} = \left(\frac{\partial G}{\partial x} \right) \otimes I$$

Sharp brightness changes lie on curves in img called edges; made of edge pts

Gradient based edge following

Alg. 5.1

* find high mag gradient points

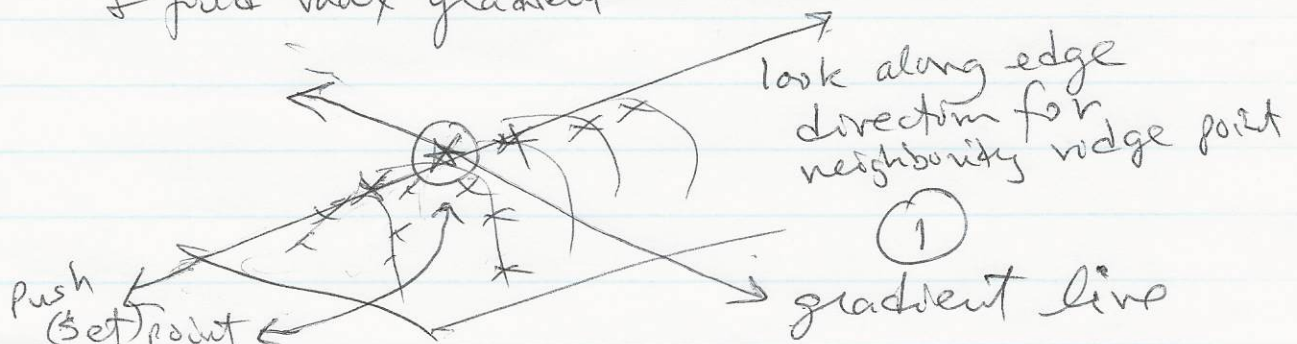
e.g., $[rows, cols] = \text{find}(\text{mag} > \text{THRESH1});$
 \uparrow

* keep track of visited pixels gradient magnitude image

* pick a point

* look in gradient direction (both sides)

+ find max gradient



* Expand chain at that point

+ look along \perp to gradient (both ways)

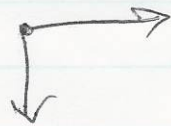
+ check for max (at that location)

along its gradient direction

+ check max is above THRESH2

* push point into stack

Corners :



Give (x, y, θ)
pose

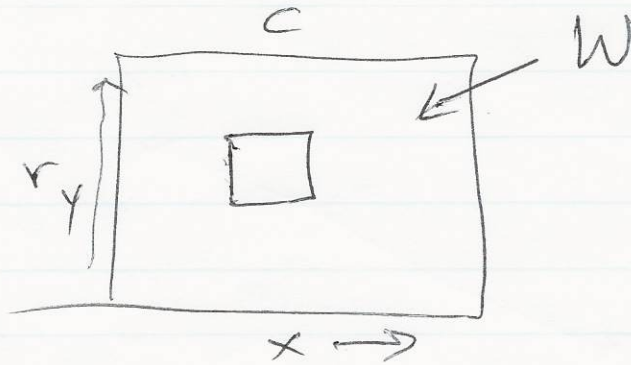
Find corner: find edge curves, then find corners where direction changes

Harris corner detector

Moravec proposed:

$$E(u, v) = \sum_x \sum_y w(x, y) [I(x+u, y+v) - I(x, y)]^2$$

At every pixel: i.e., there's an $E_{x, y, c}(u, v)$



Harris showed:

Taylor expansion of $I(x+u, y+v) = I(x, y) + u f_x(x, y) + v f_y(x, y)$

Substitute: (omit w for now)

$$\begin{aligned} E(u, v) &= \sum_{x, y} [I(x, y) + u f_x(x, y) + v f_y(x, y) - I(x, y)]^2 \\ &= \sum_{x, y} [u^2 f_x^2(x, y) + 2uv f_x(x, y) f_y(x, y) + v^2 f_y^2(x, y)] \\ &= \sum_{x, y} \left[\begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} f_x^2 & f_x f_y \\ f_x f_y & f_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} \right] \\ &= \begin{bmatrix} u & v \end{bmatrix} \left(\sum_{x, y} \begin{bmatrix} f_x^2 & f_x f_y \\ f_x f_y & f_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix} \end{aligned}$$

Let $M = \sum_{x, y} w(x, y) \begin{bmatrix} f_x^2 & f_x f_y \\ f_x f_y & f_y^2 \end{bmatrix}$ for gradient:
 just the covariance matrix

So just get all dx, dy "pts" from window

$$\text{pts} = \begin{bmatrix} dx_1 & dy_1 \\ dx_2 & dy_2 \\ \vdots & \vdots \\ dx_n & dy_n \end{bmatrix}$$

Find covariance matrix:

$$M = \text{pts}' * \text{pts};$$

$$H = M \quad (H \text{ from text})$$

corner response, R , at each pixel (r, c) :

$$R(r, c) = \det(H) - 0.05 * \text{trace}(H)_{1,2}$$

Matlab example A5 dir

Section 5.3.2 Neighborhood

5)5

The weights w may all be 1 (above)
or like a 2D Gaussian

$$\text{Laplacian: } (\nabla^2 f)(x, y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

smooth first (why?): Gaussian

So Laplacian of Gaussian of image
log

Laplacian

Consider $\nabla^2 f = \frac{\partial^2 f}{\partial x^2}$ template $[-1 \ 1]$
for $\partial f / \partial x$

$$\text{Let } \frac{\partial f}{\partial x}(r, c) = f(r, c+1) - f(r, c)$$

$$\frac{\partial f}{\partial x}(r, c-1) = f(r, c) - f(r, c-1)$$

$$\text{So, } \frac{\partial}{\partial x} \left(\frac{\partial f}{\partial x}(r, c-1) \right) = (f(r, c+1) - f(r, c)) - (f(r, c) - f(r, c-1))$$

$$= f(r, c+1) - 2f(r, c) + f(r, c-1)$$

template $[1 \ -2 \ 1]$

likewise $\frac{\partial}{\partial y} \left(\frac{\partial f}{\partial y}(r-1, c) \right) = f(r-1, c) - 2f(r, c) + f(r+1, c)$

template: $\begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$

Can do both at once (add them)

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \text{or} \quad \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

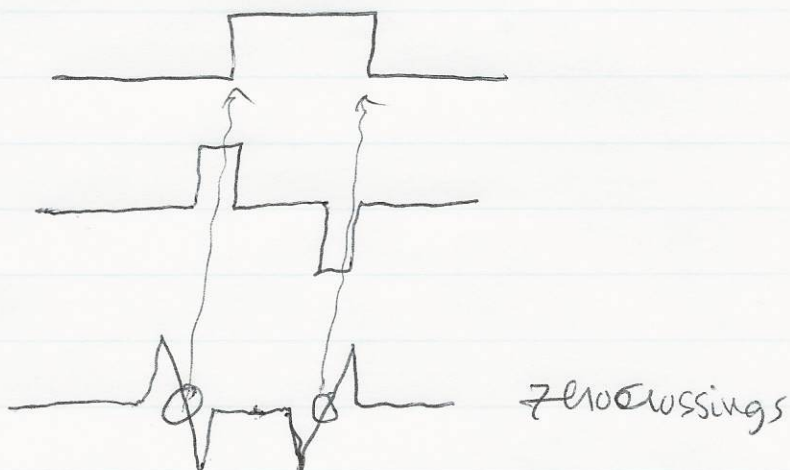
look at f special ('laplacian', 0, 000001);
may use opposite sign

the Laplacian can be applied across several scales (spatial resolution)

Consider f :

$$\frac{\partial f}{\partial x}$$

$$\frac{\partial^2 f}{\partial x^2}$$



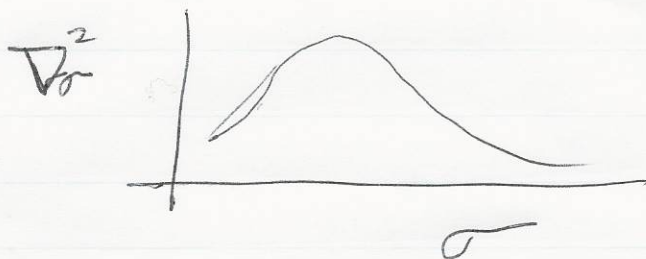
(line 108 in .m file)

Can use Laplacian across scale to find interesting points:

Figure 5.12 shows corner point and how

$$r(x, y) = \underset{\sigma}{\operatorname{argmax}} \nabla_{\sigma}^2 I(x, y)$$

100 b2



line 116 in A4.m

Can find max r at every pixel, & then pick local maxima spatially

line 13 in A6.m

use a local spatial max (+ maybe a threshold)
to get spatial + scale maxima as
interest points.

Ab: Part I: implement Alg. 5.2

Fix scale k

Apply corner detector

initialize list of patches

for each corner detected

(x_c, y_c) is location of corner

$$r(x_c, y_c) = \underset{\sigma}{\operatorname{argmax}} \nabla_{\sigma}^2 I(x_c, y_c)$$

don't
interpolate + find
max; use fine
 σ spacing

$H(\theta)$ = orientation histogram

within radius $k \cdot r$ of x_c, y_c

$$\theta_p = \underset{\theta}{\operatorname{argmax}} H(\theta)$$

$[x_c, y_c, r, \theta_p]$ output

Ab: Part II: implement Alg. 5.2 + 5.3

Assume fixed scale k

$(x_c, y_c, r) \leftarrow$ position and scale local extrema

for each tuple

$H(\theta) \leftarrow$ histogram gradient orientations radiuses $k \cdot r$

$$\theta_p \leftarrow \underset{\theta}{\operatorname{argmax}} H(\theta)$$

$[x_c, y_c, r, \theta_p] \leftarrow$ output