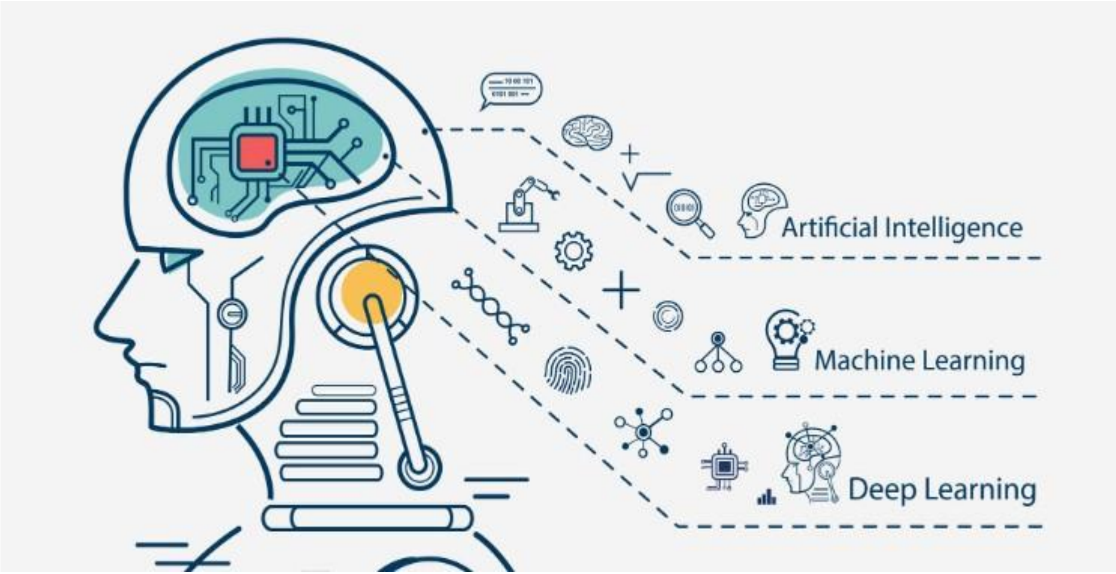
Image processing and Computer Vision



Mentors -:
Akshat Agarwal(200081)
Subhrajit Mishra(201006)

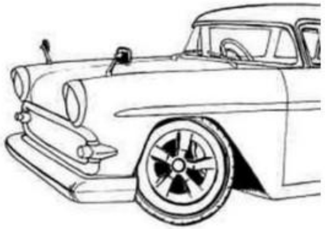
Edge detection

- Who am I?

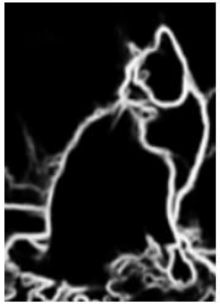
many

few, dim

non-uniform



patchy



mewww~

- It implies: edges convey a lot of info.
- Lossy but extremely high compression

What makes edges

- Discontinuity in color
- Change in surface normal
- Change in illumination
- Depth discontinuity
- Reflectance change
- Inoculation is an edge itself!

What makes edges

- Discontinuity in color
- Change in surface normal
- Change in illumination
- Depth discontinuity
- Reflectance change
- Inoculation is an edge itself!

Edge

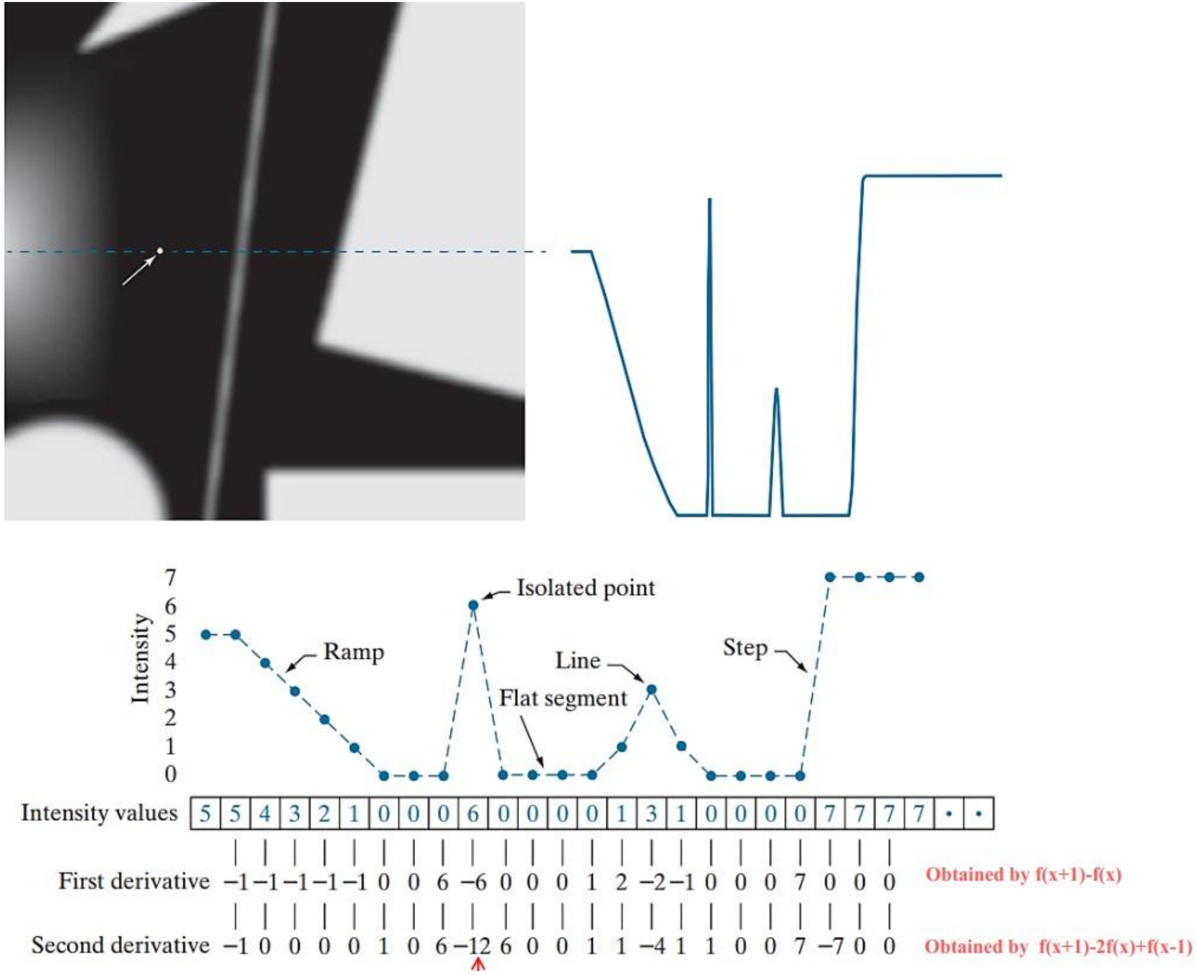
- Forward $$\frac{\partial f(x)}{\partial x} = f'(x) = f(x+1) - f(x)$$
- Backward $$\frac{\partial f(x)}{\partial x} = f'(x) = f(x) - f(x-1)$$
- Central $$\frac{\partial f(x)}{\partial x} = f'(x) = \frac{f(x+1) - f(x-1)}{2}$$
- 2nd order central $$\frac{\partial^2 f(x)}{\partial x^2} = f''(x) = f(x+1) - 2f(x) + f(x-1)$$

- Image $f(x, y)$

$$\frac{\partial^2 f(x,y)}{\partial x^2} = f(x+1,y) - 2f(x,y) + f(x-1,y)$$

$$\frac{\partial^2 f(x,y)}{\partial y^2} = f(x,y+1) - 2f(x,y) + f(x,y-1)$$

Edge



Isolated point
Ramp
Line
Flat segment
Step
Intensity
7
6
5
4
3
2
1
0
Intensity values 5 5 4 3 2 1 0 0 0 6 0 0 0 0 1 3 1 0 0 0 0 7 7 7 7 • •
First derivative −1 −1 −1 −1 −1 0 0 6 −6 0 0 0 1 2 −2 −1 0 0 0 7 0 0 0
Second derivative −1 0 0 0 0 1 0 6 −12 6 0 0 1 1 −4 1 1 0 0 7 −7 0 0
Obtained by f(x+1)-f(x)
Obtained by f(x+1)-2f(x)+f(x-1)

Point

- Isolated point
  - 2^{nd} derivatives
  - Laplacian

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

$$\frac{\partial^2 f}{\partial x^2} = f(x+1,y) + f(x-1,y) - 2f(x,y)$$

$$\frac{\partial^2 f}{\partial y^2} = f(x,y+1) + f(x,y-1) - 2f(x,y)$$

$$\nabla^2 f(x,y) = f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1) - 4f(x,y)$$

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

Edge

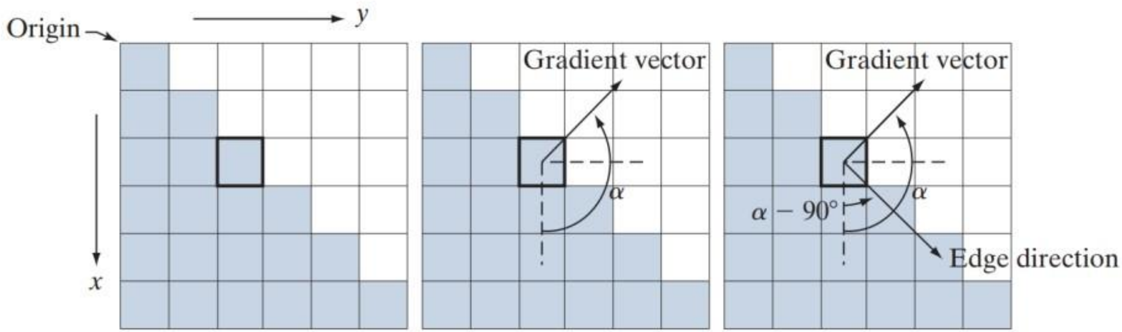
- Gradients

$$\nabla f(x,y) \equiv \text{grad}[f(x,y)] \equiv \begin{bmatrix} g_x(x,y) \\ g_y(x,y) \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f(x,y)}{\partial x} \\ \dfrac{\partial f(x,y)}{\partial y} \end{bmatrix}$$

$$M(x,y) = \|\nabla f(x,y)\| = \sqrt{g_x^2(x,y) + g_y^2(x,y)}$$

$$\alpha(x,y) = \tan^{-1}\left[\frac{g_y(x,y)}{g_x(x,y)}\right]$$

$$M(x,y) \approx |g_x| + |g_y|$$



Edge

- Sobel operator
  - derivatives via kernel
  - separable
  - diagonal direction points are not greatly discriminatory

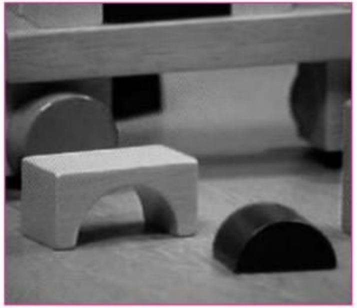
$$M_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \quad M_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

$$M = \sqrt{(M_x^2 + M_y^2)}$$

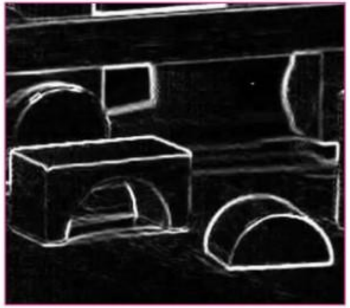
$$\theta = \tan^{-1}(M_y, M_x)$$

High robustness to noise

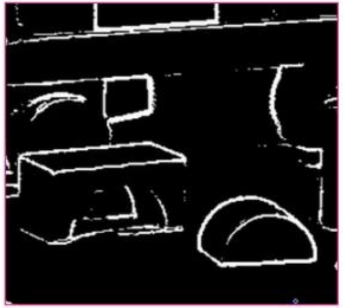
Input



M



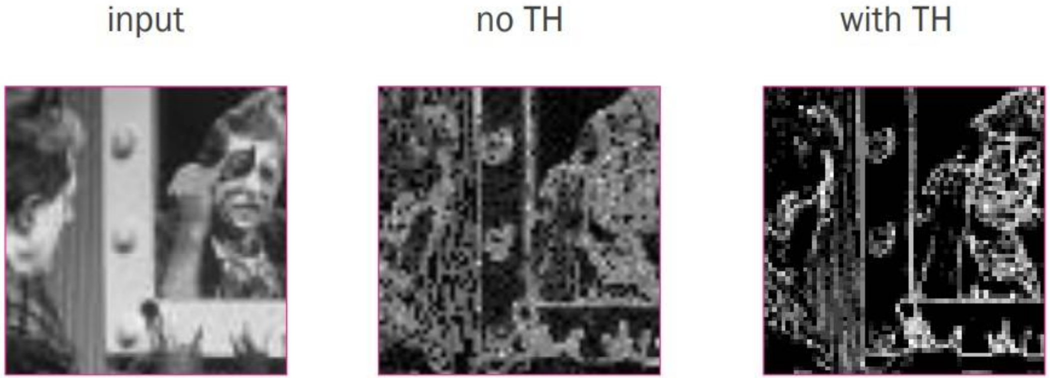
Threshold on M



Edge

- Roberts operator
  - discriminatory diagonals
  - fast

$$M_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad M_y = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$$

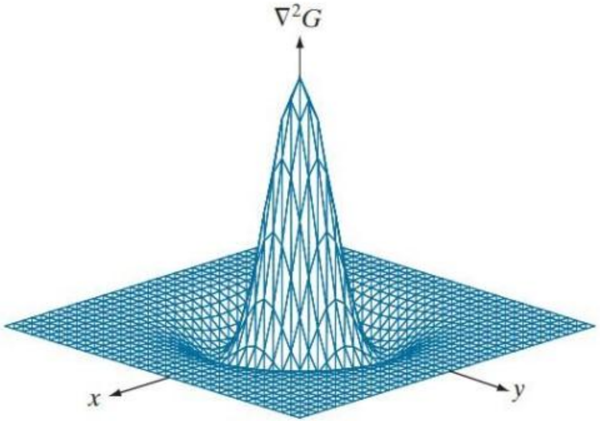


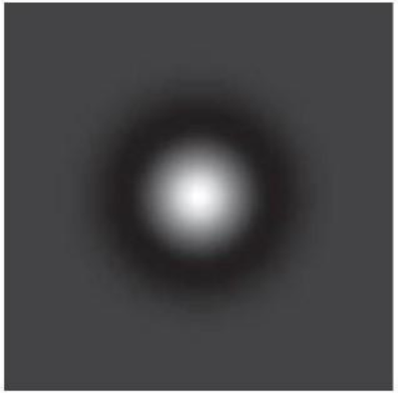
Edge

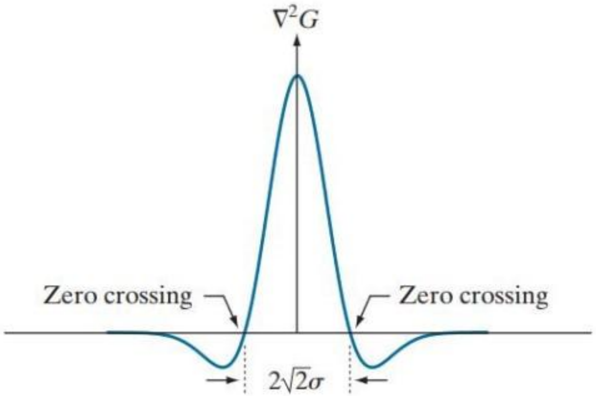
- LoG
  - Laplacian of Gaussian
  - for convenience negative of LoG are plotted

$$g(x,y) = \left[\nabla^2 G(x,y)\right] \star f(x,y)$$

$$g(x,y) = \nabla^2 \left[G(x,y) \star f(x,y)\right]$$







0	0	−1	0	0
0	−1	−2	−1	0
−1	−2	16	−2	−1
0	−1	−2	−1	0
0	0	−1	0	0

Edge

- LoG

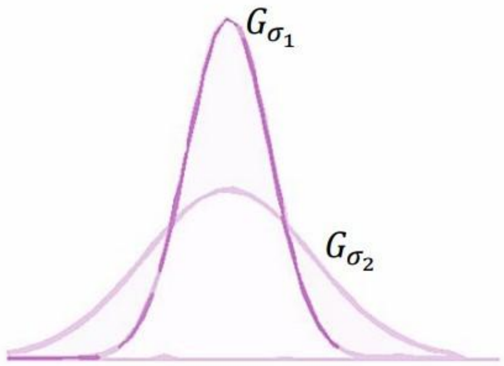
input

LoG

zero crossings

Edge

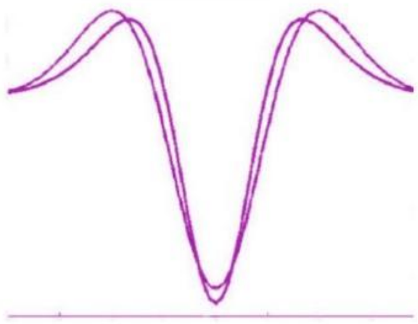
- LoG are approximately DoGs
  - to speed up computations



$$\text{LoG}: \ \Delta^2 G_\sigma \approx G_{\sigma_1} - G_{\sigma_2}$$

- What is the best DOG?
  - the one who obeys the LoG closely

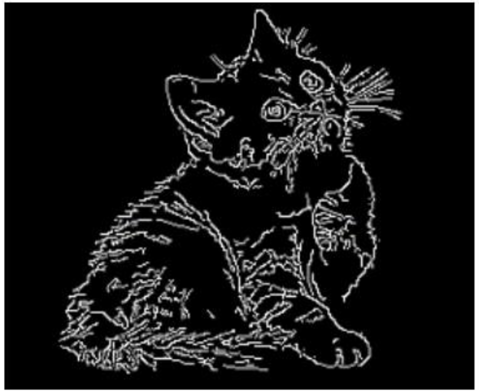
$$\sigma_1 = \frac{\sigma}{\sqrt{2}} \qquad \sigma_2 = \sqrt{2}\,\sigma$$



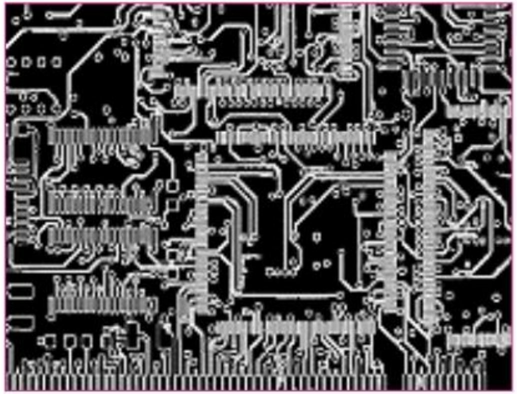
- Single point thick edges

input

Canny edges

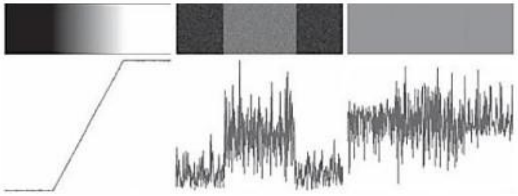


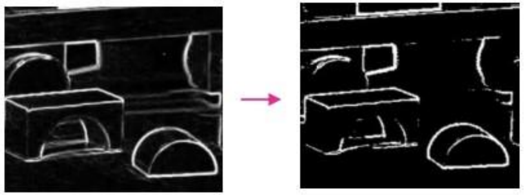
Canny PCB edges

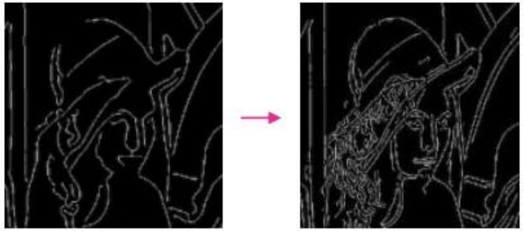


Edge

- What would be important steps in edge det.
  - Smooth derivatives
  - Thresholding
  - Thinning
  - Linking







Canny edge detector

- Image derivatives
  - input image $f(x, y)$
  - smoothed $f_s(x, y)$
  - any operator can be used to get $g_x(x, y)$, $g_y(x, y)$

$$G(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$$

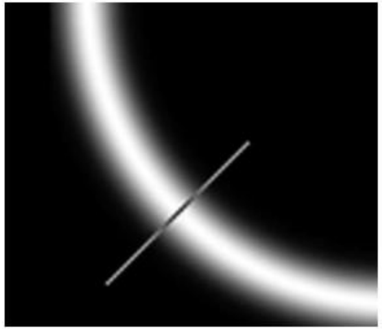
$$f_s(x,y) = G(x,y) \star f(x,y)$$

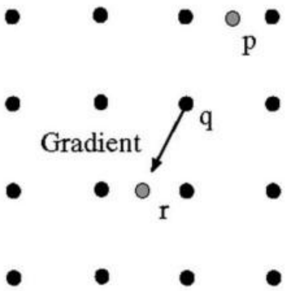
$$g_x(x,y) = \partial f_s(x,y)/\partial x \qquad g_y(x,y) = \partial f_s(x,y)/\partial y$$

$$M_s(x,y) = \|\nabla f_s(x,y)\| = \sqrt{g_x^2(x,y) + g_y^2(x,y)} \qquad \alpha(x,y) = \tan^{-1}\left[\frac{g_y(x,y)}{g_x(x,y)}\right]$$

Canny edge detector

- Thinning
  - non-max suppression:
    checks whether pixel is local maxima in grad direction
  - linear interpolation for missing locations e.g. r, p

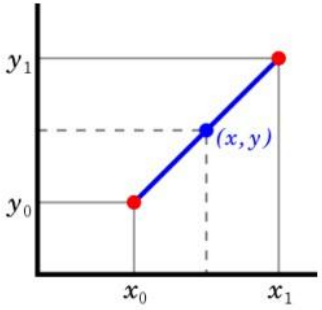




$$\frac{y - y_0}{x - x_0} = \frac{y_1 - y_0}{x_1 - x_0}$$

$$y = y_0 + (x - x_0)\frac{y_1 - y_0}{x_1 - x_0}$$

$$= y_0\left(1 - \frac{x - x_0}{x_1 - x_0}\right) + y_1\left(\frac{x - x_0}{x_1 - x_0}\right)$$



Canny edge detector

- Varying σ

input

σ small

σ large

Canny edge detector

- Comparing other edge detectors

input

Sobel with TH

LoG zero crossings

Canny

Thank you!