

- 1.
- a) Canny is a non isotropic, LOG is isotropic
 - b) Canny is computed in terms of 1st order derivative
LOG is computed in terms of 2nd order derivative
 - c) Canny need the parameters of σ and two thresholds for hysteresis
LOG need σ defining the scale of Gaussian blurring
 - d) Canny is more likely to produce long thin contours because of non-maximum suppression which thins and hysteresis thresholding which can fill in weak edge gaps.

2. rotational invariance LBP,

Let (P, R) denote a circulate neighborhood, P is a number of sampling points and R is the radius

$$(x_p, y_p) = (x + R \cos(\frac{2\pi p}{P}), y - R \sin(\frac{2\pi p}{P}))$$

$$LBP_{P,R}(x, y) = \sum_{p=0}^{P-1} s(f(x, y) - f(x_p, y_p)) \cdot 2^p$$

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$$

- b) Let $U_P(n, r)$ be a uniform LBP pattern, $I^{\theta_0}(x, y)$ be the rotation of image $I(x, y)$ by θ degrees, denote (x', y') as (x, y) over rotate, $I^{\theta_0}(x', y') = I(x, y)$, if there are P points in LBP, $\theta = \frac{k \cdot 360^\circ}{P}$, $k = 0, 1, \dots, P-1$

something rotated by $P+1$ steps will yield the same pattern as one rotated by 1 step, due to rotation symmetry.

$$U_P(n, r) = U_P(n, r + k \bmod P)$$

$$h_b(U_P(n, r + k)) = (U_P(n, r))$$

3. a) matrix-vector

$$p(f) = \frac{\sqrt{\det B}}{\sqrt{(2\pi)^m}} \exp\left(-\frac{(f-M)^T B (f-M)}{2\sigma^2}\right)$$
 f is an $m \times 1$ vector, x is an $m \times 1$ vector

b) metropolis sampling

f is initialize Randomly, S is image lattice

For $i \in S$

$f'_{i'} = f_i$, for all $i' \neq i$, choose $f_i \in \mathcal{L}$ at random, $p = \min\{1, \frac{p(f')}{p(f)}\}$

Replace f by f' with probability p , generate a uniform random

variable $u \in (0, 1)$. if $u \leq p$ replace f by f' , if $u > p$, no change

c) Gibbs sampling.

Let f be a random configuration, For $i \in S$ do: compute $p_i = p(f_i = 1 / f_{N_i})_{\mathcal{L}}$
 where f_{N_i} are the pixel values at neighboring sites $\in \mathcal{L}$

set f_i to 1 with probability p_i ~~the~~

4. a) (ii), (iv)

b) (ii)

c) (iiv)

d) (iv)

e) (iiv)

5. first, forward pass

$$\begin{aligned} \text{net input } h_1 &= w_1 \times i_1 + w_2 \times i_2 + b_1 \times 1 \\ &= 0.15 \times 0.05 + 0.2 \times 0.1 + 0.35 \times 1 = 0.3775 \end{aligned}$$

$$\text{out } h_1 = \frac{1}{1 + e^{-\text{net } h_1}} = \frac{1}{1 + e^{-0.3775}} = 0.5933$$

$$\text{input } h_2 = 0.25 \times 0.05 + 0.30 \times 0.1 + 0.35 \times 1 = 0.3925$$

$$\text{out } h_2 = \frac{1}{1 + e^{-0.3925}} = 0.59688$$

$$\begin{aligned} \text{input } o_1 &= w_5 \times \text{out } h_1 + w_6 \times \text{out } h_2 + b_2 \times 1 \\ &= 0.4 \times 0.5933 + 0.45 \times 0.59688 + 0.6 \times 1 = 1.10591 \end{aligned}$$

$$\text{out } o_1 = \frac{1}{1 + e^{-\text{net } o_1}} = \frac{1}{1 + e^{-1.10596}} = 0.75136$$

$$\text{input } o_2 = 0.5 \times 0.5933 + 0.55 \times 0.59688 + 0.6 \times 1 = 1.2249$$

$$\text{out } o_2 = \frac{1}{1 + e^{-1.2249}} = 0.77293$$

$$E_{\text{total}} = \sum \frac{1}{2} (\text{target} - \text{output})^2$$

$$E_{o_1} = \frac{1}{2} (0.01 - 0.75136)^2 = 0.2798$$

$$E_{o_2} = \frac{1}{2} (0.99 - 0.77293)^2 = 0.02356$$

$$E_{\text{total}} = E_{o_1} + E_{o_2} = 0.27981 + 0.02356 = 0.29837$$

$$W_6^* = W_6 - \eta \times \left(\frac{\partial E_{\text{total}}}{\partial W_6} \right)$$

$$\frac{\partial E_{\text{total}}}{\partial W_6} = \frac{\partial E_{\text{total}}}{\partial \text{out } o_1} \times \frac{\partial \text{out } o_1}{\partial \text{net } o_1} \times \frac{\partial \text{net } o_1}{\partial W_6}$$

$$\frac{\partial E_{\text{total}}}{\partial \text{out } o_1} = -(\text{target } o_1 - \text{out } o_1) = -(0.01 - 0.75136) = 0.741365$$

$$\frac{\partial \text{out } o_1}{\partial \text{net } o_1} = \text{out } o_1 (1 - \text{out } o_1) = 0.75136 \times (1 - 0.751365) = 0.18682$$

$$\frac{\partial \text{net } o_1}{\partial W_6} = (1 \times \text{out } h_2 \times W_6^{(1-9)}) + 0 + 0 = \text{out } h_2 = 0.59688$$

$$\therefore W_6^* = 0.59688 - 0.5 \times 0.741365 \times 0.18682 \times 0.59688 = 0.408666$$

$$W_2^* = W_2 - \eta \times \frac{\partial E_{\text{total}}}{\partial W_2}$$

$$\frac{\partial E_{\text{total}}}{\partial W_2} = \frac{\partial E_{\text{total}}}{\partial \text{out } h_2} \times \frac{\partial \text{out } h_2}{\partial \text{net } h_2} \times \frac{\partial \text{net } h_2}{\partial W_2}$$

$$\begin{aligned} \frac{\partial E_{\text{total}}}{\partial \text{out } h_2} &= \frac{\partial E_{o_1}}{\partial \text{out } h_2} + \frac{\partial E_{o_2}}{\partial \text{out } h_2} = \frac{\partial E_{o_1}}{\partial \text{net } o_1} \times \frac{\partial \text{net } o_1}{\partial \text{out } h_2} + \frac{\partial E_{o_2}}{\partial \text{net } o_2} \times \frac{\partial \text{net } o_2}{\partial \text{out } h_2} \\ &= \frac{\partial E_{o_1}}{\partial \text{out } h_2} \times \frac{\partial \text{out } h_2}{\partial \text{net } o_1} \times \frac{\partial \text{net } o_1}{\partial \text{out } h_2} + \frac{\partial E_{o_2}}{\partial \text{net } o_2} \times \frac{\partial \text{out } h_2}{\partial \text{net } o_2} \times \frac{\partial \text{net } o_2}{\partial \text{out } h_2} \\ &= 0.041371 \end{aligned}$$

$$\frac{\partial \text{outh}_2}{\partial \text{net}_2} = \text{outh}_2 (1 - \text{outh}_2) = 0.59688 \times (1 - 0.59688) = 0.240614$$

$$\frac{\partial \text{net}_2}{\partial W_2} = \hat{v}_2 = 0.1$$

$$\therefore W_2^* = 0.20 - 0.5 \times 0.041371 \times 0.240614 \times 0.1 = 0.199561$$