



CAP 5415 Computer Vision Fall 2005

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www.cs.ucf.edu/courses/cap5415/fall2005

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Recap (Edge Detection)

- Prewitt and Sobel edge detectors
 - Compute derivatives
 - In x and y directions
 - Find gradient magnitude
 - Threshold gradient magnitude
- Difference between Prewitt and Sobel is the derivative filters

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Prewitt Edge Detector

Prewitt's
edges in x
direction

$$\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \rightarrow I_x$$

Prewitt's
edges in y
direction

$$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \rightarrow I_y$$

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Sobel Edge Detector



Sobel's
edges in x
direction

$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \rightarrow I_x$$



Sobel's
edges in y
direction

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \rightarrow I_y$$



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Edge Detection Continued

- Marr Hildreth Edge Detector
- Canny Edge Detector

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Marr Hildreth Edge Detector

- Smooth image by Gaussian filter $\rightarrow S$
- Apply Laplacian to S
 - Used in mechanics, electromagnetics, wave theory, quantum mechanics and Laplace equation
- Find zero crossings
 - Scan along each row, record an edge point at the location of zero-crossing.
 - Repeat above step along each column

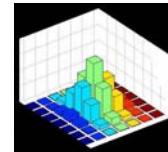
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Marr Hildreth Edge Detector

- Gaussian smoothing

$$\text{smoothed image } \hat{S} = \text{Gaussian filter } g * \text{image } I$$
$$g = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$



- Find Laplacian

$$\Delta^2 S = \overbrace{\frac{\partial^2}{\partial x^2} S}^{\text{second order derivative in } x} + \overbrace{\frac{\partial^2}{\partial y^2} S}^{\text{second order derivative in } y}$$

- ∇ is used for gradient (derivative)
- Δ is used for Laplacian

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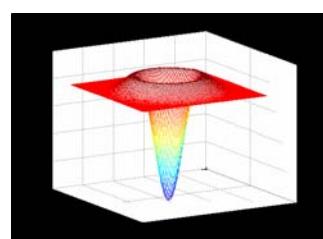
Marr Hildreth Edge Detector

- Deriving the Laplacian of Gaussian (LoG)

$$\Delta^2 S = \Delta^2(g * I) = (\Delta^2 g) * I$$

Homework

$$\Delta^2 g = -\frac{1}{\sqrt{2\pi}\sigma^3} \left(2 - \frac{x^2 + y^2}{\sigma^2} \right) e^{-\frac{x^2+y^2}{2\sigma^2}}$$



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LoG Filter

$$\Delta^2 G_\sigma = -\frac{1}{\sqrt{2\pi}\sigma^3} \left(2 - \frac{x^2 + y^2}{\sigma^2} \right) e^{-\frac{x^2+y^2}{2\sigma^2}}$$

0.0008	0.0066	0.0215	0.031	0.0215	0.0066	0.0008
0.0066	0.0438	0.0982	0.108	0.0982	0.0438	0.0066
0.0215	0.0982	0	-0.242	0	0.0982	0.0215
0.031	0.108	-0.242	-0.7979	-0.242	0.108	0.031
0.0215	0.0982	0	-0.242	0	0.0982	0.0215
0.0066	0.0438	0.0982	0.108	0.0982	0.0438	0.0066
0.0008	0.0066	0.0215	0.031	0.0215	0.0066	0.0008

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Finding Zero Crossings

- Four cases of zero-crossings :
 - {+,-}
 - {+,0,-}
 - {-,+}
 - {-,0,+}
- Slope of zero-crossing {a, -b} is |a+b|.
- To mark an edge
 - compute slope of zero-crossing
 - Apply a threshold to slope

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On the Separability of LoG

- Similar to separability of Gaussian filter
 - Two-dimensional Gaussian can be separated into 2 one-dimensional Gaussians

$$h(x, y) = I(x, y) * g(x, y) \quad n^2 \text{ multiplications}$$

$$h(x, y) = (I(x, y) * g_1(x)) * g_2(y) \quad 2n \text{ multiplications}$$

$$g_1 = [0.011 \quad .13 \quad .6 \quad 1 \quad .6 \quad .13 \quad .011]$$

$$g_2 = \begin{bmatrix} .011 \\ .13 \\ .6 \\ 1 \\ .6 \\ .13 \\ .011 \end{bmatrix}$$

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On the Separability of LoG

$$\Delta^2 S = \Delta^2(g * I) = (\Delta^2 g) * I = I * (\Delta^2 g)$$

Requires n^2 multiplications

$$\Delta^2 S = (I * g_{xx}(x)) * g(x) + (I * g_{yy}(y)) * g(y)$$

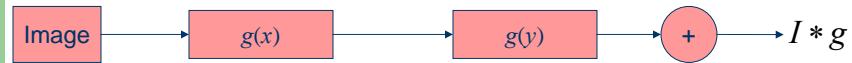
Requires $4n$ multiplications

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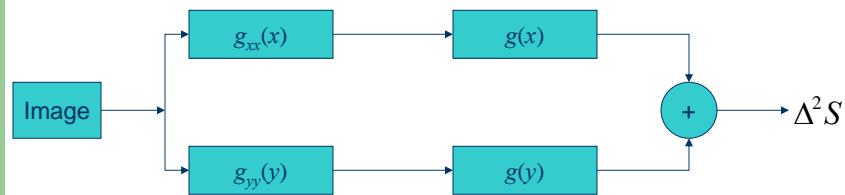


Seperability

Gaussian Filtering



Laplacian of Gaussian Filtering



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Example

I



$I * (\Delta^2 g)$



Zero crossings of $\Delta^2 S$

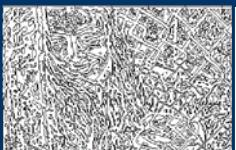


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Example

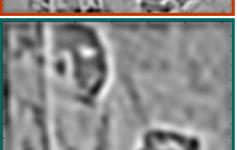
$\sigma = 1$



$\sigma = 3$



$\sigma = 6$



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Algorithm

- Compute LoG
 - Use 2D filter $\Delta^2 g(x, y)$
 - Use 4 1D filters $g(x), g_{xx}(x), g(y), g_{yy}(y)$
- Find zero-crossings from each row
- Find slope of zero-crossings
- Apply threshold to slope and mark edges

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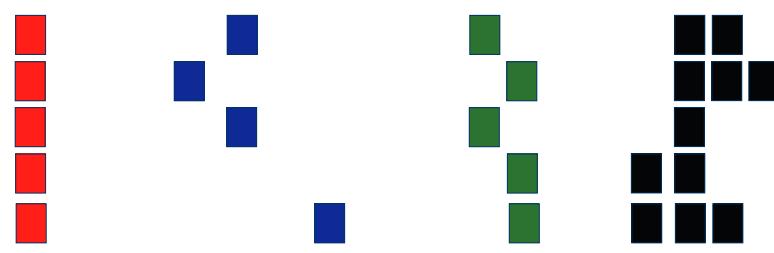
Quality of an Edge

- Robust to noise
- Localization
- Too many or too less responses

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Quality of an Edge



True
edge

Poor robustness
to noise

Poor
localization

Too many
responses

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Canny Edge Detector

- Criterion 1: Good Detection: The optimal detector must minimize the probability of false positives as well as false negatives.
- Criterion 2: Good Localization: The edges detected must be as close as possible to the true edges.
- Single Response Constraint: The detector must return one point only for each edge point.

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Canny Edge Detector Steps

1. Smooth image with Gaussian filter
2. Compute derivative of filtered image
3. Find magnitude and orientation of gradient
4. Apply “Non-maximum Suppression”
5. Apply “Hysteresis Threshold”

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Canny Edge Detector First Two Steps

- Smoothing

$$S = I * g(x, y) = g(x, y) * I$$

$$g(x, y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- Derivative

$$\nabla S = \nabla(g * I) = (\nabla g) * I$$

$$\nabla S = \begin{bmatrix} g_x \\ g_y \end{bmatrix} * I = \begin{bmatrix} g_x * I \\ g_y * I \end{bmatrix}$$

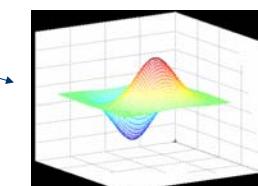
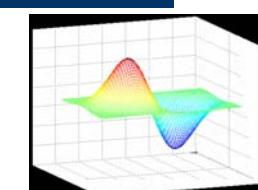
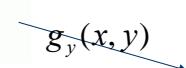
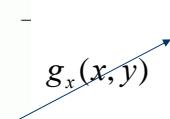
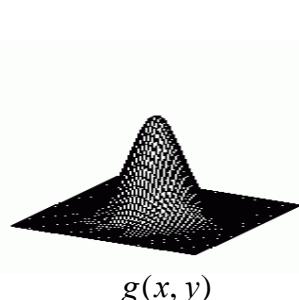
Homework

$$\nabla g = \begin{bmatrix} \frac{\partial g}{\partial x} \\ \frac{\partial g}{\partial y} \end{bmatrix} = \begin{bmatrix} g_x \\ g_y \end{bmatrix}$$

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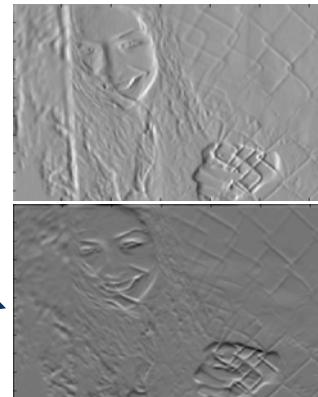
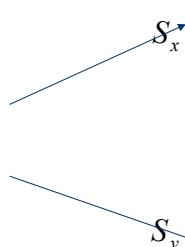
Canny Edge Detector Derivative of Gaussian



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Canny Edge Detector First Two Steps



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Canny Edge Detector Third Step

- Gradient magnitude and gradient direction

(S_x, S_y) Gradient Vector

$$\text{magnitude} = \sqrt{(S_x^2 + S_y^2)}$$

$$\text{direction} = \theta = \tan^{-1} \frac{S_y}{S_x}$$



image

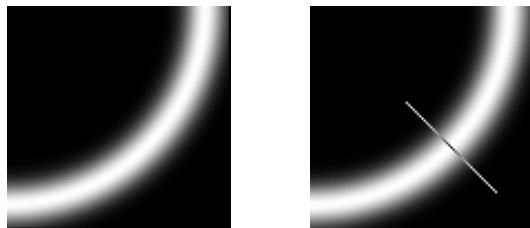
gradient magnitude

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Canny Edge Detector Fourth Step

- Non maximum suppression



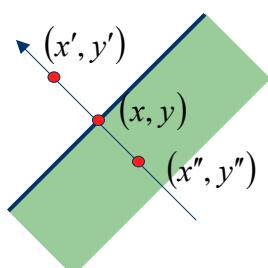
We wish to mark points along the curve where the **magnitude is biggest**. We can do this by looking for a maximum along a slice normal to the curve (non-maximum suppression). These points should form a curve. There are then two algorithmic issues: at which point is the maximum, and where is the next one?

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Canny Edge Detector Non-Maximum Suppression

- Suppress the pixels in $|\nabla S|$ which are not local maximum



$$M(x, y) = \begin{cases} |\nabla S|(x, y) & \text{if } |\Delta S|(x, y) > |\Delta S|(x', y') \\ & \quad \& |\Delta S|(x, y) > |\Delta S|(x'', y'') \\ 0 & \text{otherwise} \end{cases}$$

x' and x'' are the neighbors of x along normal direction to an edge

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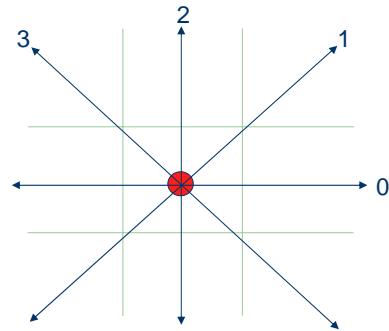


Canny Edge Detector Quantization of Normal Directions

$$\tan \theta = \frac{S_y}{S_x}$$

Quantizations :

- 0: $-0.4142 < \tan \theta \leq 0.4142$
- 1: $0.4142 < \tan \theta < 2.4142$
- 2: $|\tan \theta| \geq 2.4142$
- 3: $-2.4142 < \tan \theta \leq -0.4142$



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Canny Edge Detector Non-Maximum Suppression

$$|\Delta S| = \sqrt{S_x^2 + S_y^2}$$



For visualization
 $M \geq \text{Threshold} = 25$



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Canny Edge Detector Hysteresis Thresholding

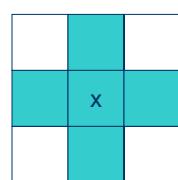
- If the gradient at a pixel is
 - above “**High**”, declare it an ‘edge pixel’
 - below “**Low**”, declare it a “**non-edge-pixel**”
 - **between** “low” and “high”
 - Consider its neighbors iteratively then declare it an “edge pixel” if it is **connected** to an ‘edge pixel’ **directly** or via pixels **between** “low” and “high”.

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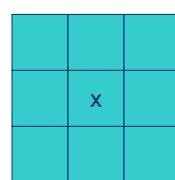


Canny Edge Detector Hysteresis Thresholding

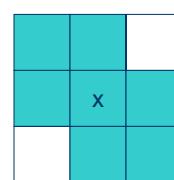
- Connectedness



4 connected



8 connected

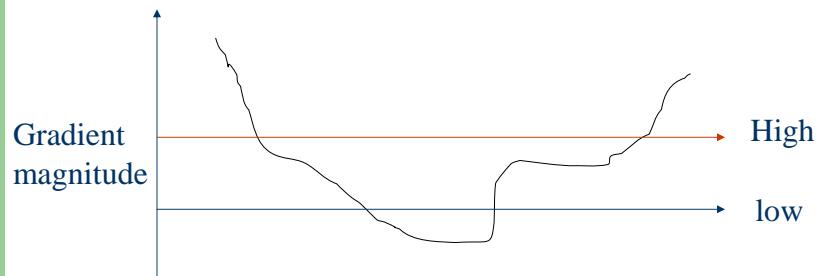


6 connected

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Canny Edge Detector Hysteresis Thresholding



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Canny Edge Detector Hysteresis Thresholding

- Scan the image from left to right, top-bottom.
 - The gradient magnitude at a pixel is above a high threshold declare that as an edge point
 - Then recursively consider the *neighbors* of this pixel.
 - If the gradient magnitude is above the low threshold declare that as an edge pixel.

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Canny Edge Detector Hysteresis Thresholding



M

regular
 $M \geq 25$



Hysteresis
High = 35
Low = 15



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Homework

1. Derive Laplacian of Gaussian
2. Drive gradient of 2D Gaussian
3. Show that gradient magnitude is rotation invariant.

- Due date 28 September 2005

$$g = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

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Programming Project 1

- Implement Canny Edge Detector
- Deliverables
 - Short report, problems, results, program code, etc.
 - Step by step outputs of images
 - Program code
 - Program should ask for a PGM image from user
 - Ask for the threshold value, sigma of Gaussian
 - Write out or display the image
- Due Date 17 October 2005

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Suggested Reading

- Chapter 4, Emanuele Trucco, Alessandro Verri, "Introductory Techniques for 3-D Computer Vision"
- Chapter 2, Mubarak Shah, "Fundamentals of Computer Vision"

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