Edge Detection and Corner Detection

Computer Vision I
CSE 252A
Lecture 6
Announcements

• Assignment 1 is due Oct 20, 11:59 PM
• Assignment 2 will be released Oct 20
  – Due Nov 3, 11:59 PM
• Reading:
  – Szeliski
    • Sections 7.2 and 7.1.1
Image Segmentation and Edges

- Image Segmentation is the process of dividing an image into connected regions such that pixels within a region share certain characteristics (color, texture, brightness, etc.)

- Boundaries or edges divide segmented regions.

[From Berkeley Segmentation Dataset] 13 Regions
Image Segmentation

[From Berkeley Segmentation Dataset]
Related Topics:
Semantic and Instance Segmentation
Edges in Natural Images

Source: Photografr.com
What Causes an Edge?

- Depth discontinuity
- Surface orientation discontinuity
- Illumination discontinuity (e.g., shadow)
- Specular reflection of other discontinuity
- Reflectance discontinuity (i.e., change in surface material properties)

Source: Photografr.com
Noisy 1D Step Edge

- Derivative is high everywhere.
- Must smooth before taking gradient.
Edge is Where Change Occurs: 1-D

• Change is measured by derivative in 1D

- Ideal Edge
- Smoothed Edge
- First Derivative
- Second Derivative

• Biggest change, first derivative has maximum magnitude
• Or second derivative is zero
Numerical Derivatives of Sampled Signal

Take Taylor series expansion of \( f(x) \) about \( x_0 \)
\[
f(x) = f(x_0) + f'(x_0)(x-x_0) + \frac{1}{2} f''(x_0)(x-x_0)^2 + \ldots
\]

Consider samples taken at increments of \( h \) and first two terms of the expansion, we have
\[
f(x_0+h) = f(x_0) + f'(x_0)h + \frac{1}{2} f''(x_0)h^2
\]
\[
f(x_0-h) = f(x_0) - f'(x_0)h + \frac{1}{2} f''(x_0)h^2
\]
Subtracting and adding \( f(x_0+h) \) and \( f(x_0-h) \) respectively yields
\[
f'(x_0) = \frac{f(x_0 + h) - f(x_0 - h)}{2h}
\]
\[
f''(x_0) = \frac{f(x_0 + h) - 2f(x_0) + f(x_0 - h)}{h^2}
\]

Convolve with

First Derivative: \([-1/2h \ 0 \ 1/2h]\)
Second Derivative: \([1/h^2 \ -2/h^2 \ 1/h^2]\)
Numerical Derivatives

Convolution kernel
First Derivative: \([-1/2h \ 0 \ 1/2h]\)
Second Derivative: \([1/h^2 \ -2/h^2 \ 1/h^2]\)

- With images, units of \(h\) is pixels, so \(h=1\)
  - First derivative: \([-1/2 \ 0 \ 1/2]\)
  - Second derivative: \([1 \ -2 \ 1]\)

- When computing derivatives in the \(x\) and \(y\) directions, use these convolution kernels:

\[
\frac{d}{dx} = \begin{bmatrix} -1/2 & 0 & 1/2 \end{bmatrix} \quad \frac{d}{dy} = \begin{bmatrix} -1/2 \\ 0 \\ 1/2 \end{bmatrix}
\]
Implementing 1D Edge Detection

1. Filter out noise: convolve with Gaussian
2. Take a derivative: convolve with [1 0 -1]
   We can combine steps 1 and 2
3. Find the peaks of $|df/dx|$

Two issues:
- Should be a local maximum of $|df/dx|$ 
- Should be greater than a threshold: $|df/dx| > \tau$
2D Edge Detection

1. Filter out noise
   - Use a 2D Gaussian Filter.

2. Take a derivative \( J = I \otimes G \)
   - Compute the magnitude of the gradient:

\[
\nabla J = (J_x, J_y) = \left( \frac{\partial J}{\partial x}, \frac{\partial J}{\partial y} \right)
\]

\[
\| \nabla J \| = \sqrt{J_x^2 + J_y^2}
\]

\[
\tan^{-1} \left( \frac{J_y}{J_x} \right)
\]

the direction of the gradient
Smoothing and Differentiation

- Need two derivatives, in x and y direction.
- Filter with Gaussian and then compute Gradient, OR
- Use a derivative of Gaussian filter
  - because differentiation is convolution, and convolution is associative
Directional Derivatives

\[
\frac{\partial G_\sigma}{\partial x} \quad \frac{\partial G_\sigma}{\partial y}
\]

\[
\cos \theta \frac{\partial G_\sigma}{\partial x} + \sin \theta \frac{\partial G_\sigma}{\partial y}
\]
Finding derivatives

Is this $dI/dx$ or $dI/dy$?
There are three major issues:

1. The gradient magnitude at different scales is different; which scale should we choose?
2. The gradient magnitude is large along a thick trail; how do we identify the significant points?
3. How do we link the relevant points up into curves?
There is ALWAYS a tradeoff between smoothing and good edge localization!

- **Image with Edge (No Noise)**
- **Edge Location**
- **Image + Noise**
- **Derivatives detect edge and noise**
- **Smoothed derivative removes noise, but blurs edge**
The scale of the smoothing filter affects derivative estimates
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: which point is the maximum, and where is the next point on the curve?
Non-maximum suppression

Using normal at q, find two points p and r on adjacent rows (or columns)

q is a maximum if $|\nabla J(q)|$ is larger than $|\nabla J(p)|$ and $|\nabla J(r)|$

Interpolate to get values
Before Non-max Suppression

Gradient magnitude (x4 for visualization)
After non-max suppression

Gradient magnitude (x4 for visualization)
Non-maximum suppression
Predicting the next edge point

- The marked point is an edge point.
- From edge tangent (normal to gradient), predict next point along edge curve (here either r or s)
- Link together to create edge curve
Input image
Single Threshold

- When threshold is too high, important edges may be missed or be broken
- When threshold is too low, many extraneous edges, but non missed
- Hysteresis thresholding: Best of both
Hysteresis Thresholding

- Start tracking an edge chain at pixel location that is local maximum of gradient magnitude where gradient magnitude \( \tau_{\text{high}} \).
- Follow edge in direction orthogonal to gradient.
- Stop when gradient magnitude \( \tau_{\text{low}} \).
  - i.e., use a high threshold to start edge curves and a low threshold to continue them.
Single Threshold

T = 15

Hysteresis

Thresholding

Hysteresis

Thresholding

T = 5

T_h = 15, T_l = 5
Canny Edge Detection Algorithm

1. Three parameters $\sigma$, $\tau_{\text{high}}$, $\tau_{\text{low}}$
2. Filter with symmetric Gaussian of width $\sigma$
3. Compute gradient, magnitude, direction
4. Non-maximal suppression
5. Hysteresis thresholding using $\tau_{\text{high}}$, $\tau_{\text{low}}$
fine scale, high threshold
coarse scale, high high threshold
coarse scale, low high threshold
Why is Canny so Dominant

• Widely used for 30 years.
• Theory is nice
• Details are good
  • Magnitude of gradient,
  • Non-max suppression
  • Hysteresis thresholding
• Most subsequent detectors weren’t much better until learning-based detectors came along
• Code was distributed
Learning-based detectors: Not edges, but boundaries

- Brightness
- Color
- Texture
- Subjective contours
- Grouping
- Multiscale
Boundary detection

- Precision is the fraction of detections that are true positives rather than false positives, while recall is the fraction of true positives that are detected rather than missed.

Learned Edge Detectors


• Xie, Saining, and Zhuowen Tu. ." Proceedings of the IEEE international conference on computer vision. 2015.

HED Performance

Xie and Tu. "Holistically-nested edge detection." ICCV 2015
Corner Detection
Motivation: feature matching

• Panorama stitching
  – We have two images – how do we combine them?
Motivation: feature matching

• Panorama stitching
  – We have two images – how do we combine them?

Step 1: extract features
Step 2: match features
Motivation: feature matching

• Panorama stitching
  – We have two images – how do we combine them?

Step 1: Extract features in each image
Step 2: Match features across images
Step 3: Align images and determine a transformation
Image matching

by Diva Sian

by swashford
Harder case

by Diva Sian

by scgbt
Harder still?

NASA Mars Rover images
Answer below (look for tiny colored squares…)

NASA Mars Rover images with SIFT feature matches
Figure by Noah Snavely
Corners contain more info than lines

- A point on a line is hard to match
Corners contain more info than lines

- A corner is easier to match
Detection of corner-like features

• Corner
  – A rapid change of direction in a curve
  – A highly effective feature
    • Distinctive
    • Reasonably invariant to viewpoint
Corners
Detection of corner-like features

- Examine a small window over an image

The wiggly arrows indicate graphically a directional response in the detector as it moves in the three areas shown.
Detection of corner-like features

Intuition:

- Right at corner, gradient is ill-defined.
- Near corner, gradient has two different values.
Detection of corner-like features

• For each window location, compute the spatial gradient matrix

\[
M = \begin{bmatrix}
\sum_s \sum_t f_x^2(s, t) & \sum_s \sum_t f_x(s, t)f_y(s, t) \\
\sum_s \sum_t f_x(s, t)f_y(s, t) & \sum_s \sum_t f_y^2(s, t)
\end{bmatrix}
\]

where \( f_x \) is the gradient in the \( x \)-direction and \( f_y \) is the gradient in the \( y \)-direction

• Then, compute eigenvalues of spatial gradient matrix
Eigenvalues of spatial gradient matrix
Detection of corner-like features

• Shi-Tomasi corner detector
  – Run a small window over an image and compute spatial gradient matrix \( \mathbf{M} \)
  – Compute the minor eigenvalue of \( \mathbf{M} \) to compute measurement image \( R \)
  – Apply nonmaximal suppression to the measurement image \( R \)
    • Prevents corners from being too close to each other
  – Threshold resulting image \( R \) using global threshold \( T \)
    • Corner at coordinates corresponding to \( R > T \)
Corner Detection Sample Results

Threshold=25,000

Threshold=10,000

Threshold=5,000
Corner Detector: Workflow

Slide credit: http://vims.cis.udel.edu/~chandra/
Corner Detector: Workflow

Compute corner response $R(x, y)$
Corner Detector: Workflow

Take only the points of local maxima of $R(x,y)$ and threshold
Corner Detector: Workflow

Slide credit: http://vims.cis.udel.edu/~chandra/
Next Lecture

• Calibrated stereo

• Reading:
  – Szeliski
    • Sections 12.1.1 and 11.3.1