

Deep Learning for Computer Vision

Edge Detection

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Edge Detection



- Map image from 2D matrix of pixels to a set of curves or line segments or contours \Rightarrow More compact representation than pixels
- **Key idea?**

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Edge Detection

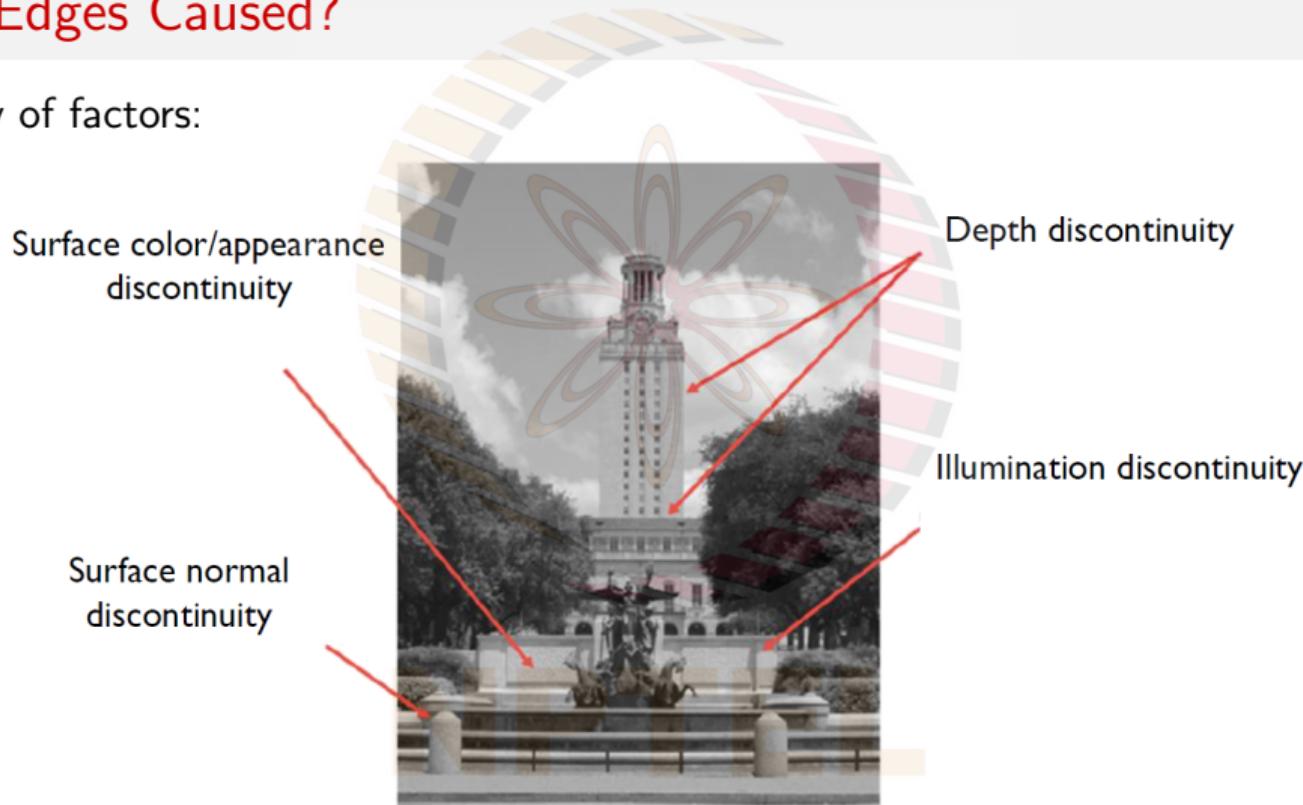


- Map image from 2D matrix of pixels to a set of curves or line segments or contours \Rightarrow More compact representation than pixels
- **Key idea?** Look for strong gradients, and then post-process

Source: Shotton, K Grauman, R Urtasun

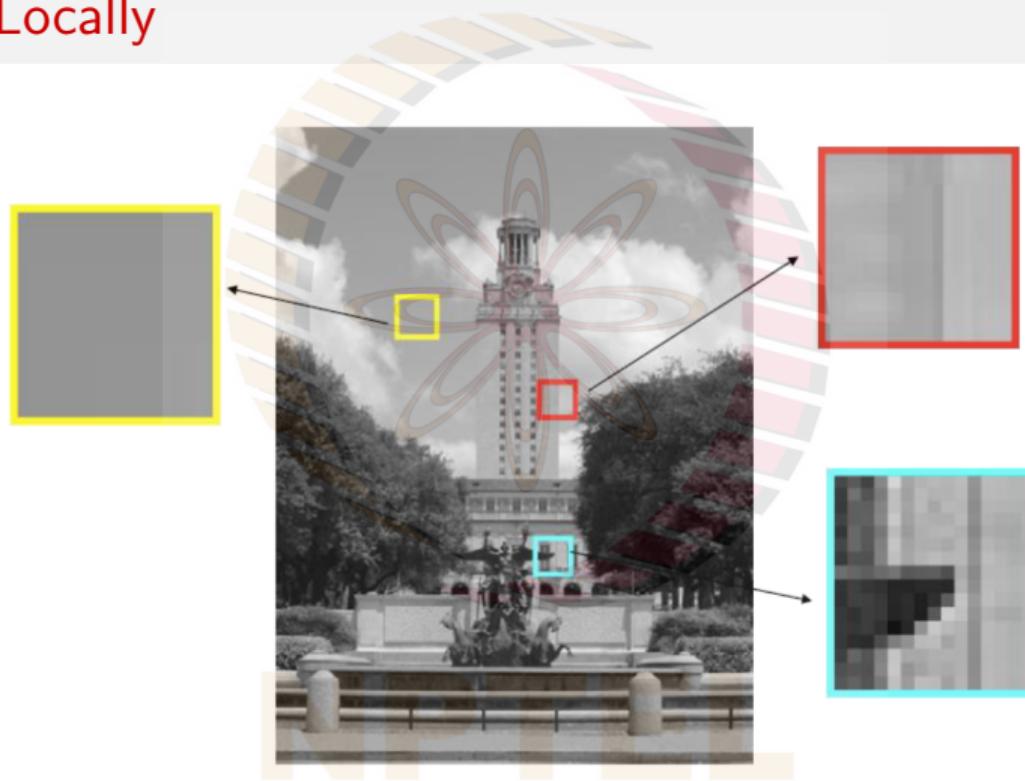
How are Edges Caused?

- Variety of factors:



Source: R Urtasun

Looking More Locally



Source: K Grauman, R Urtasun

Why are Edges Important?

- Group pixels into objects or parts
- Allow us to track important features (e.g., corners, curves, lines).
- Cues for 3D shape
- Guiding interactive image editing



Source: Derek Hoiem

Edges in Images as Functions

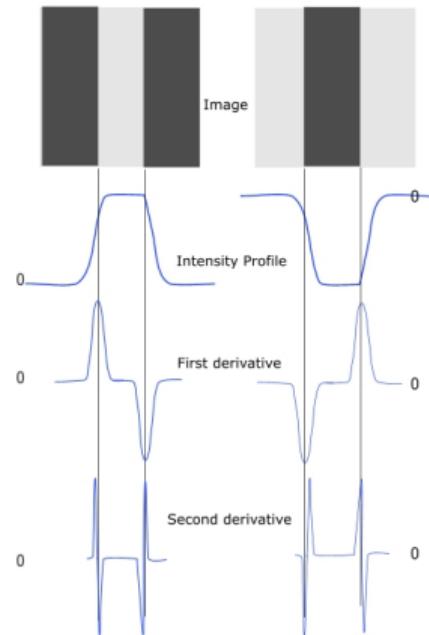
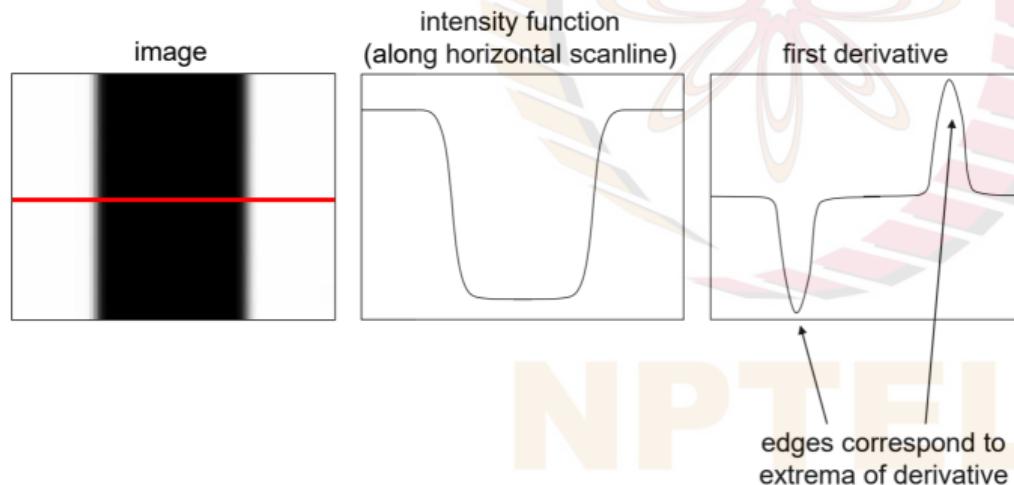
- Edges look like steep cliffs



Source: N Snavely, R Urtasun

Derivatives and Edges

- An edge is a place of rapid change in the image intensity function



Sources: L Lazebnik, K Grauman and <https://mipav.cit.nih.gov/>

Derivatives with Convolution

- For 2D function, $f(x, y)$, the partial derivative is:

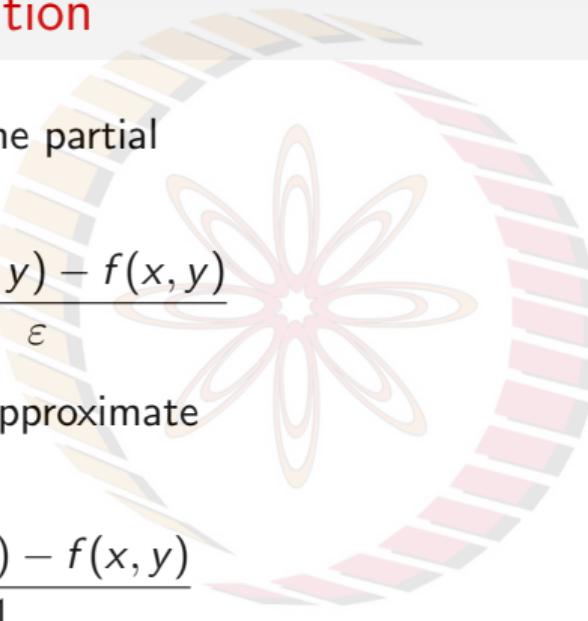
$$\frac{\partial f(x, y)}{\partial x} = \lim_{\varepsilon \rightarrow 0} \frac{f(x + \varepsilon, y) - f(x, y)}{\varepsilon}$$

- For discrete data, we can approximate using finite differences:

$$\frac{\partial f(x, y)}{\partial x} \approx \frac{f(x + 1, y) - f(x, y)}{1}$$

The NPTEL logo is a stylized, light orange text "NPTEL" with a drop shadow effect. It is overlaid on a circular decorative background featuring concentric rings of alternating light orange and pink colors, resembling a flower or a gear.

Derivatives with Convolution



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- To implement above as convolution, what would be the associated filter?

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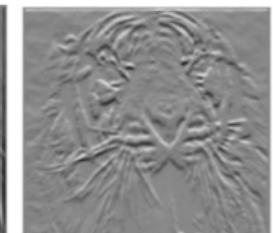
$$\frac{\partial f(x, y)}{\partial x} \approx \frac{f(x + 1, y) - f(x, y)}{1}$$

$$\frac{\partial f(x, y)}{\partial x}$$

$$\begin{matrix} -1 & 1 \end{matrix}$$



$$\frac{\partial f(x, y)}{\partial y}$$



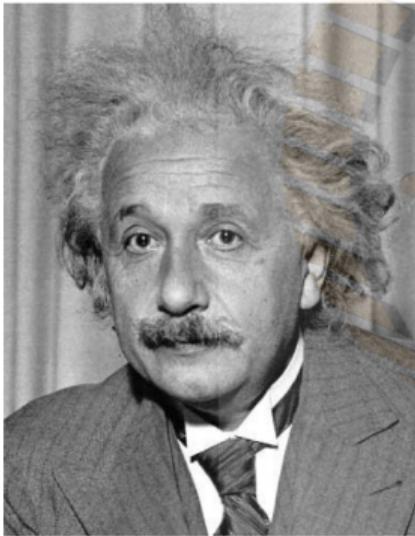
$$\begin{matrix} -1 \\ 1 \end{matrix}$$

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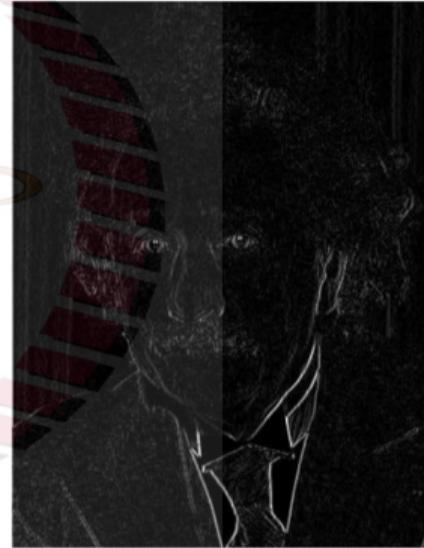
Source: K Grauman

Sobel Edge Detection Filters



1	0	-1
2	0	-2
1	0	-1

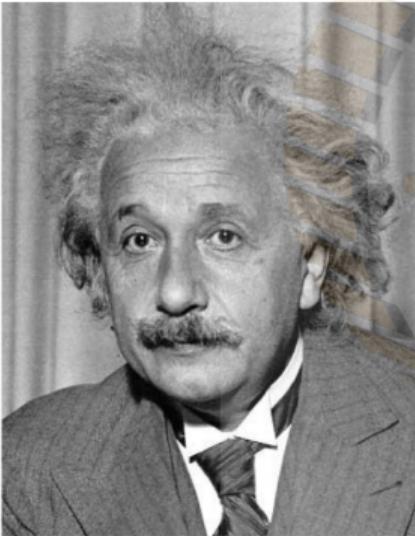
Sobel



Vertical Edge
(absolute value)

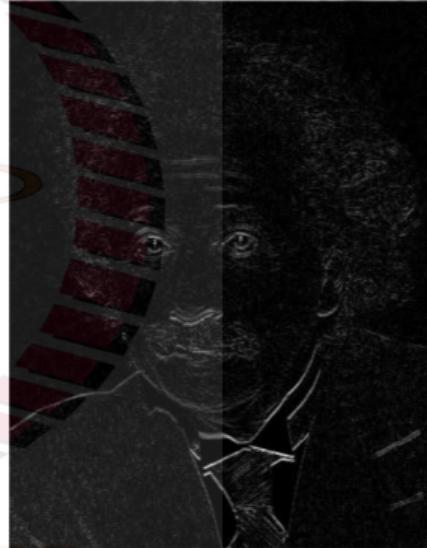
Source: J Hays

Sobel Edge Detection Filters



$$\begin{array}{ccc} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{array}$$

Sobel



Horizontal Edge
(absolute value)

Source: J Hays

Finite Difference Filters

Prewitt

$$M_x$$

-1	0	1
-1	0	1
-1	0	1

 M_y

1	1	1
0	0	0
-1	-1	-1

Sobel

-1	0	1
-2	0	2
-1	0	1

1	2	1
0	0	0
-1	-2	-1

Roberts

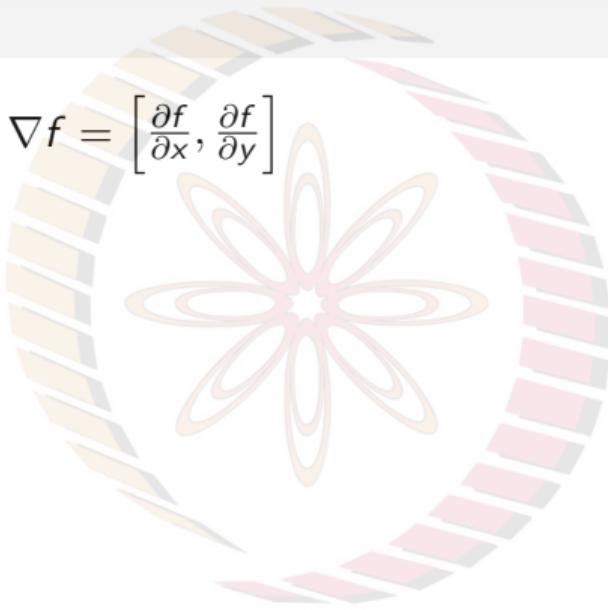
0	1
-1	0

1	0
0	-1

Source: R Urtasun

Image Gradients

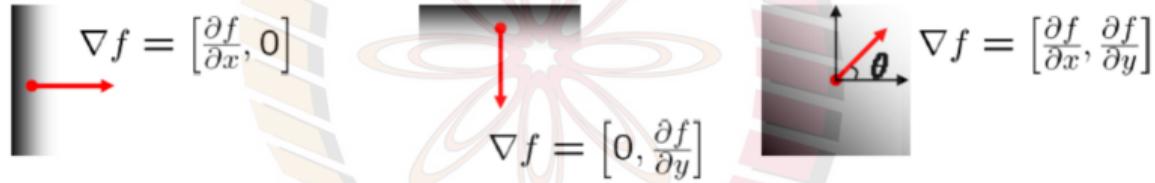
- The gradient of an image $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$



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Image Gradients

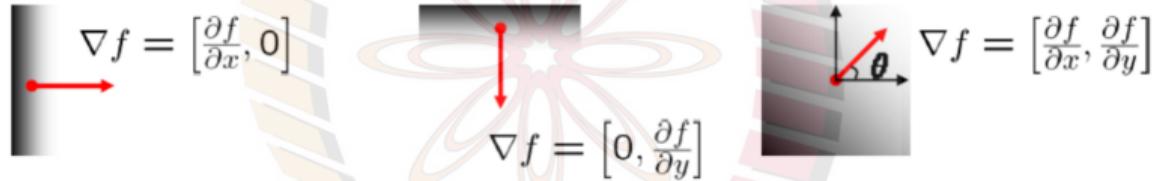
- The gradient of an image $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$
- The gradient points in the direction of most rapid change in intensity



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Image Gradients

- The gradient of an image $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$
- The gradient points in the direction of most rapid change in intensity



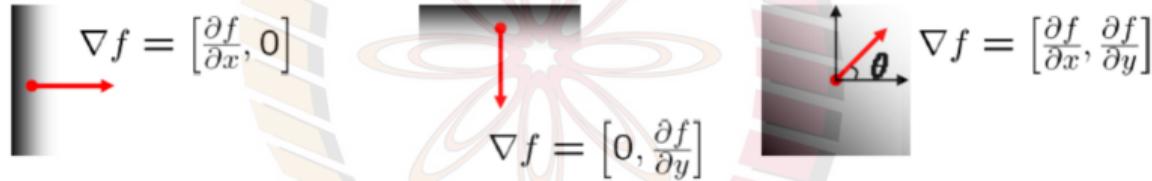
- The **gradient direction** (orientation of edge normal) is given by:

$$\theta = \tan^{-1} \left(\frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}} \right)$$

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Image Gradients

- The gradient of an image $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$
- The gradient points in the direction of most rapid change in intensity



- The **gradient direction** (orientation of edge normal) is given by:

$$\theta = \tan^{-1} \left(\frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}} \right)$$

- The **edge strength** is given by the magnitude $\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$

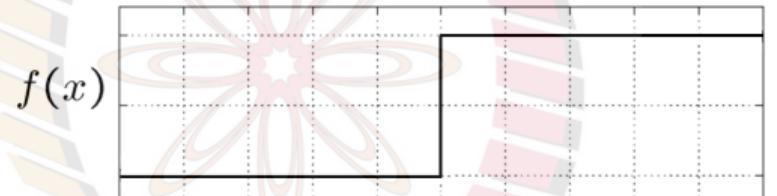
Source: S Seitz, R Urtasun

Derivative with No Noise

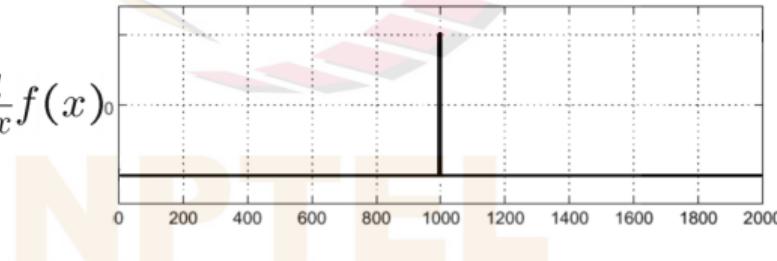
- Consider a single row or column of the image
 - Plotting intensity as a function of position gives a signal



Input image with
no noise

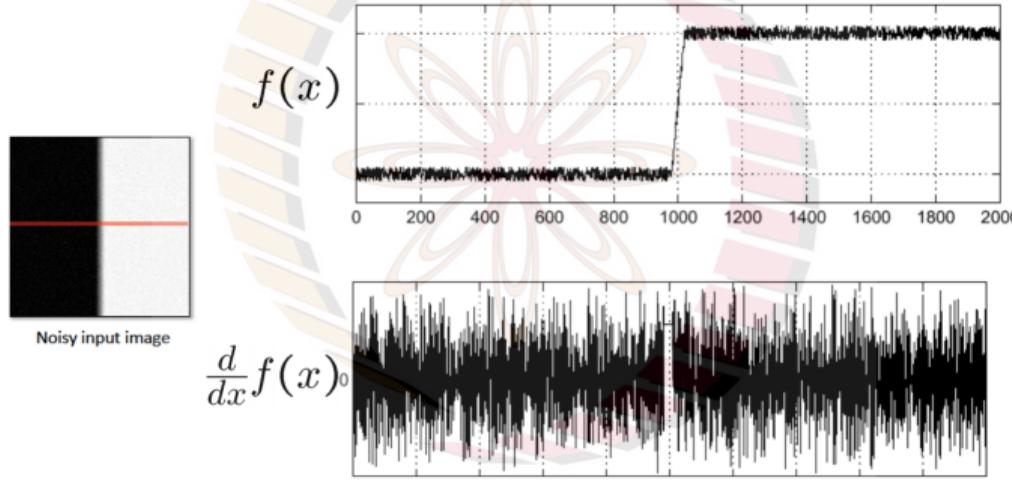


$$\frac{d}{dx}f(x)$$



Where is the edge?

Effect of Noise

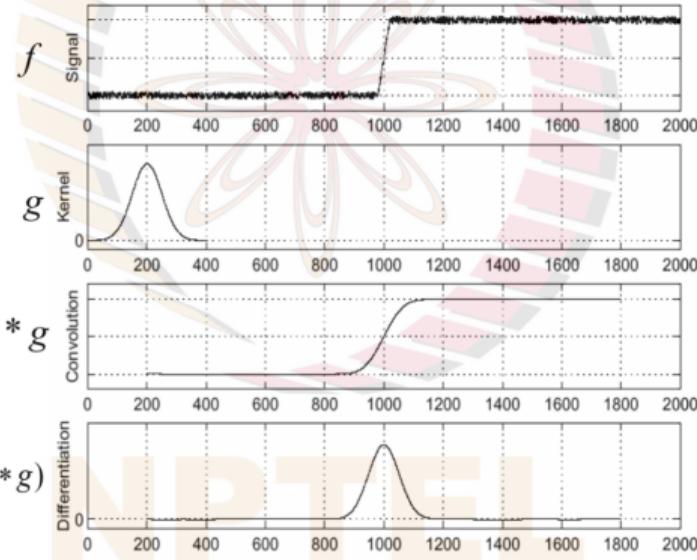


Now, where is the edge?

Source: S Seitz, K Grauman

Effect of Noise

- Smooth first, and look for peaks in $\frac{d}{dx}(f * g)$



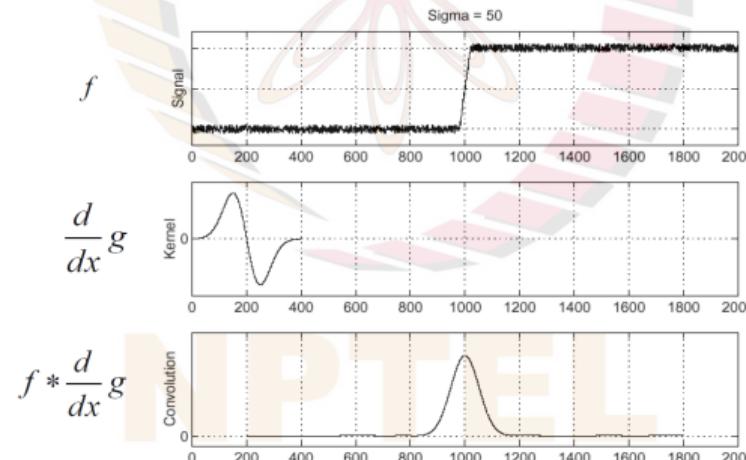
Source: S Seitz, R Urtasun

Derivative theorem of Convolution

- Differentiation is achieved through convolution, and convolution is associative:

$$\frac{d}{dx}(f * g) = f * \frac{d}{dx}g = \frac{d}{dx}f * g$$

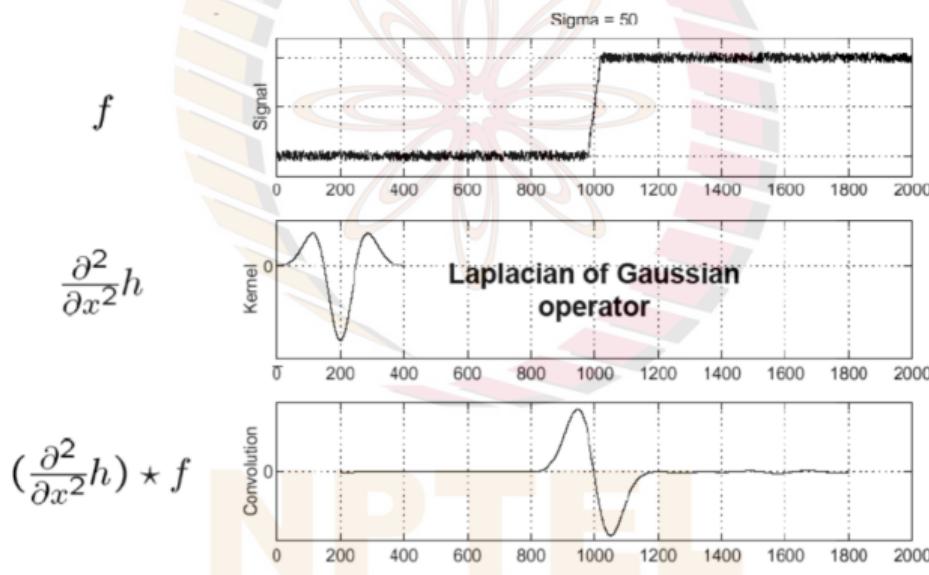
- This saves us an operation:



Source: S Seitz, R Urtasun

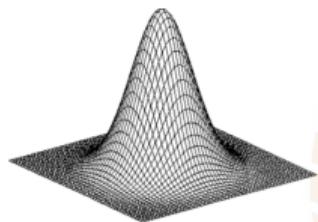
What about Second Derivative?

- Edge by detecting **zero-crossing** of bottom graph



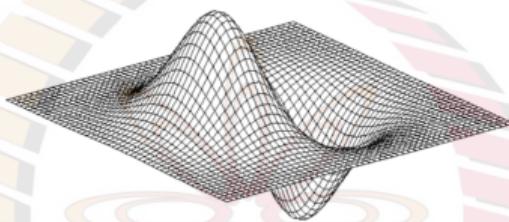
Source: S Seitz, R Urtasun

Derivative and Laplacian of Gaussians



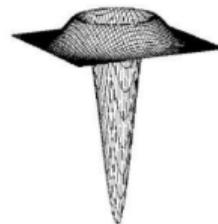
Gaussian

$$h_\sigma(x, y) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{u^2+v^2}{2\sigma^2}}$$



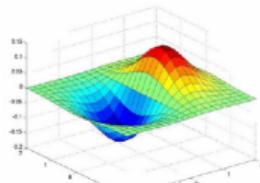
Derivative of Gaussian (x)

$$\frac{\partial}{\partial x} h_\sigma(u, v)$$

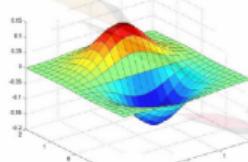


Laplacian of Gaussian

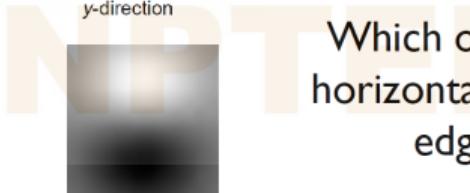
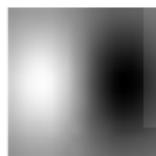
$$\nabla^2 h_\sigma(u, v)$$



x-direction



y-direction



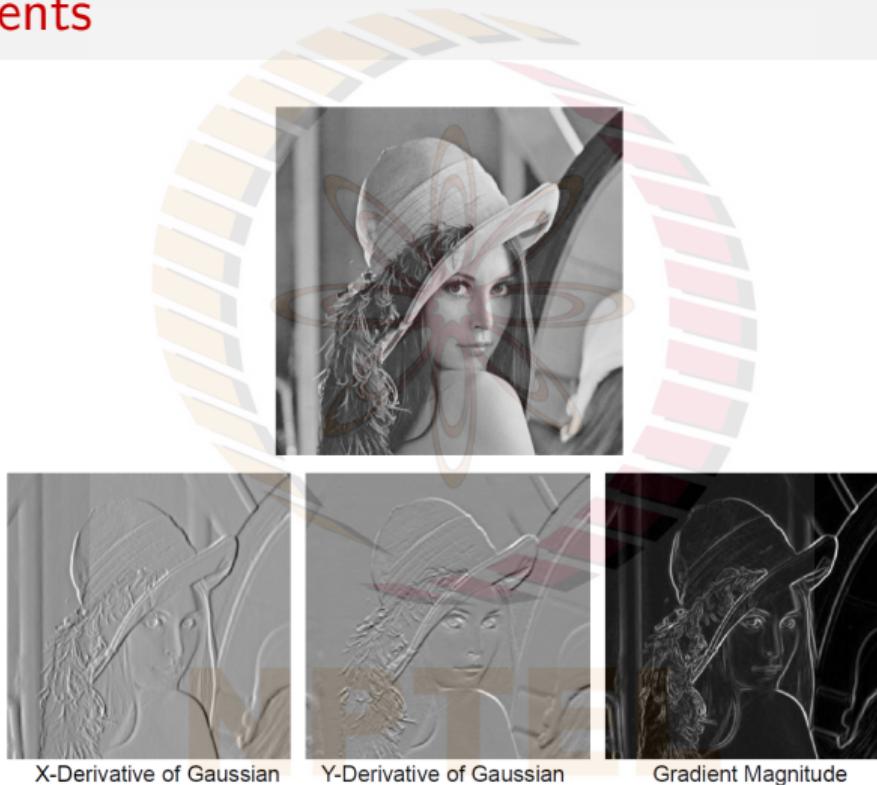
with ∇^2 the Laplacian operator

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

Which one finds
horizontal/vertical
edges?

Source: S Seitz, R Urtasun

Compute of Gradients



Source: S Seitz, R Urtasun

Properties of an Edge Detector



where is the edge?

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Properties of an Edge Detector

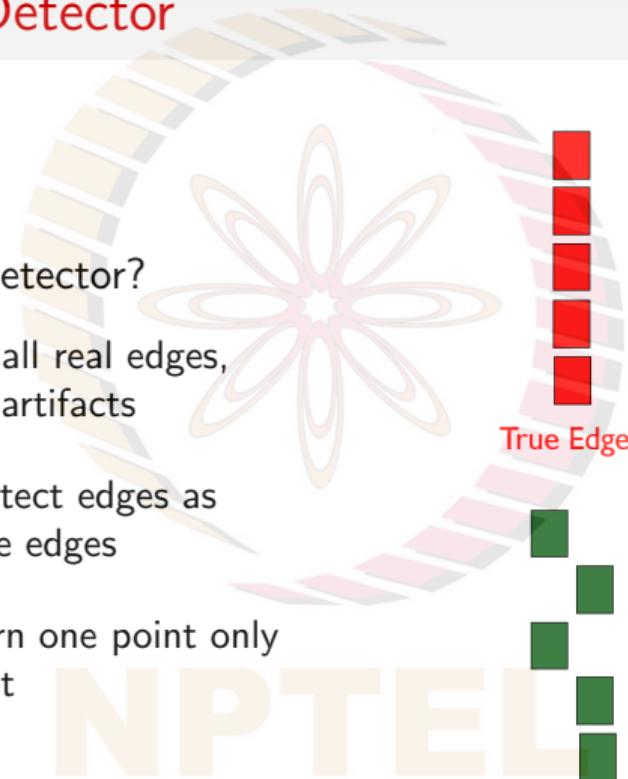
- Criteria for a good edge detector?



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Properties of an Edge Detector

- Criteria for a good edge detector?
 - Good detection:** find all real edges, ignoring noise or other artifacts
 - Good localization:** detect edges as close as possible to true edges
 - Single response:** return one point only for each true edge point



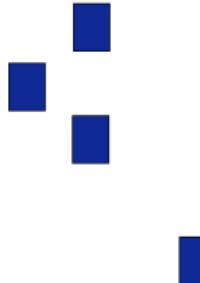
Poor localization



Poor robustness to noise



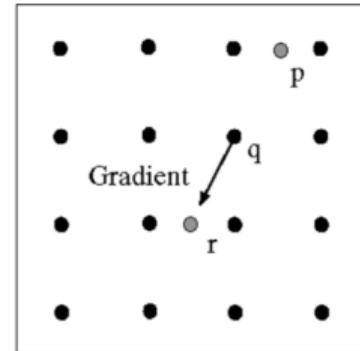
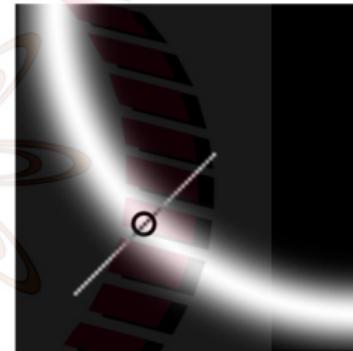
Too many responses



Non-Maxima Suppression



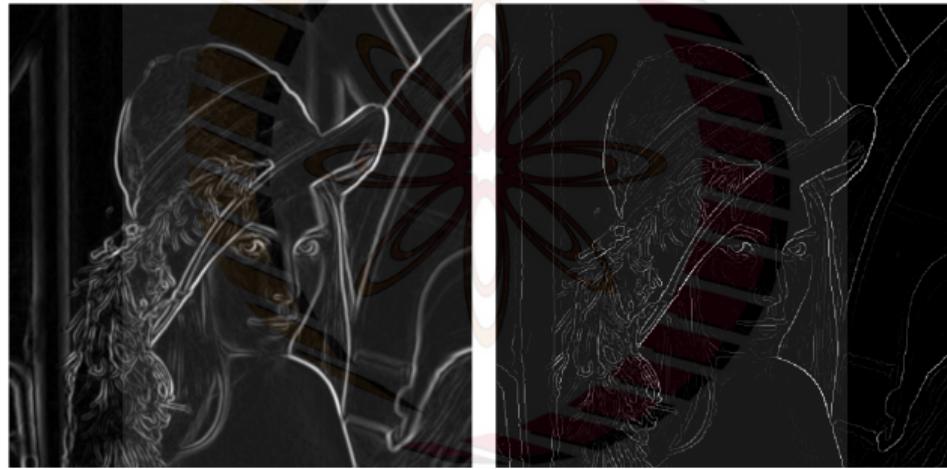
where is the edge?



- Check if pixel is local maximum along gradient direction:
 - Could require checking interpolated pixels p and r

Source: N Snavely, R Urtasun

Non-Maxima Suppression

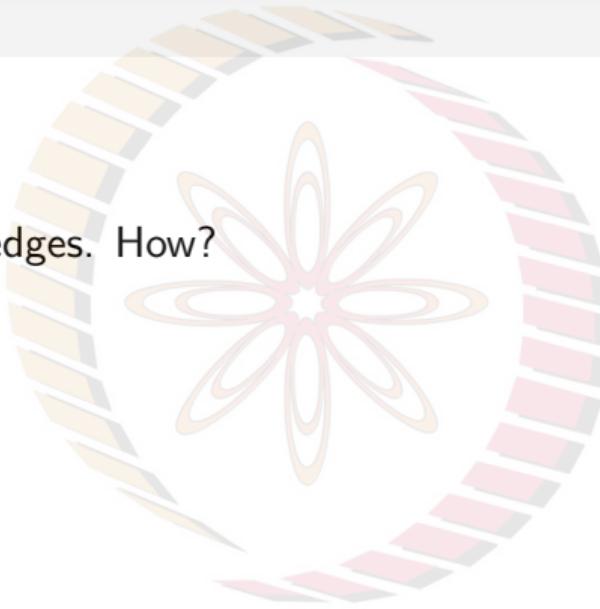


Before and after non-maxima suppression

Source: Derek Hoiem

Hysteresis Thresholding

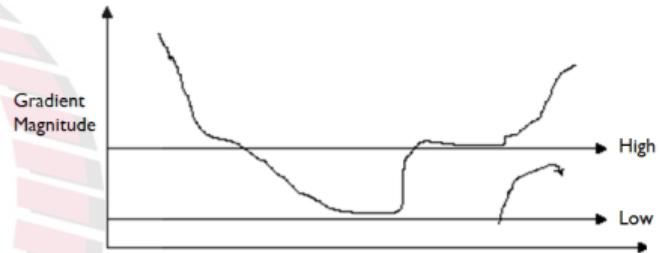
- Check for well-connected edges. How?



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Hysteresis Thresholding

- Check for well-connected edges. How?
 - Use **hysteresis**: use a *high* threshold to start edge curves and a *low* threshold to continue them.
- How does it work?
 - If gradient at pixel $>$ 'High' \Rightarrow '**edge pixel**'
 - If gradient at pixel $<$ 'Low' \Rightarrow '**non-edge pixel**'
 - If gradient at pixel \geq 'Low' and \leq 'High' \Rightarrow '**edge pixel**' iff it is connected to an 'edge pixel' directly or via pixels between 'Low' and 'High'



Source: S Seitz, R Urtasun

Canny Edge Detector

- Probably the most widely used edge detector in computer vision (Canny 1986)
- Algorithm:
 - ① Filter image with derivative of Gaussian
 - ② Find magnitude and orientation of gradient
 - ③ Non-maximum suppression
 - ④ Linking and thresholding (hysteresis):
 - Define two thresholds: low and high
 - Use the high threshold to start edge curves and the low threshold to continue them

The NPTEL logo features the letters "NPTEL" in a large, bold, sans-serif font. The letters are colored in a light beige or cream shade. Behind the letters is a circular emblem consisting of a stylized flower with eight petals, rendered in a light pink or rose color. The emblem is set against a background of horizontal stripes in shades of grey, white, and light pink.

Source: D. Lowe, L. Fei-Fei, R Urtasun

Canny Edge Pipeline and Examples

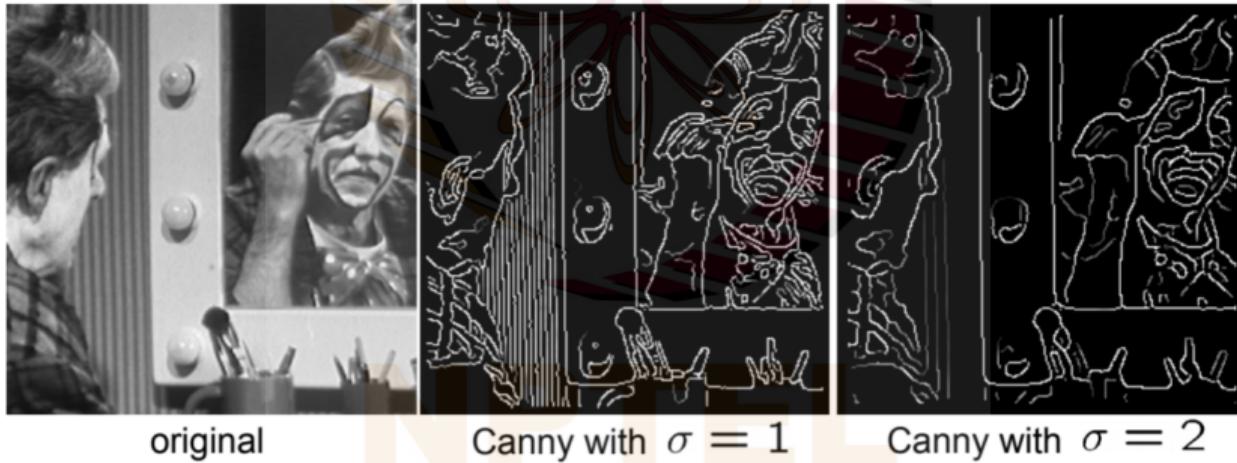


Canny Edges

Source: Prem Kalra, R Urtasun, S Fidler

Effect of σ in Canny Edge Detector

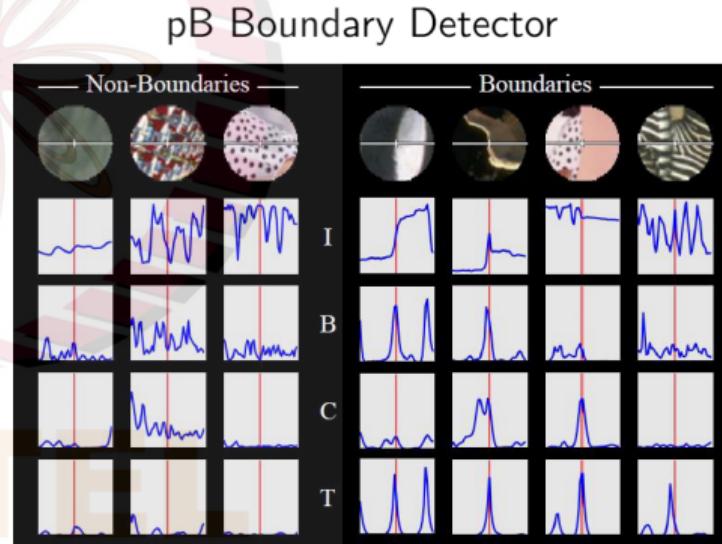
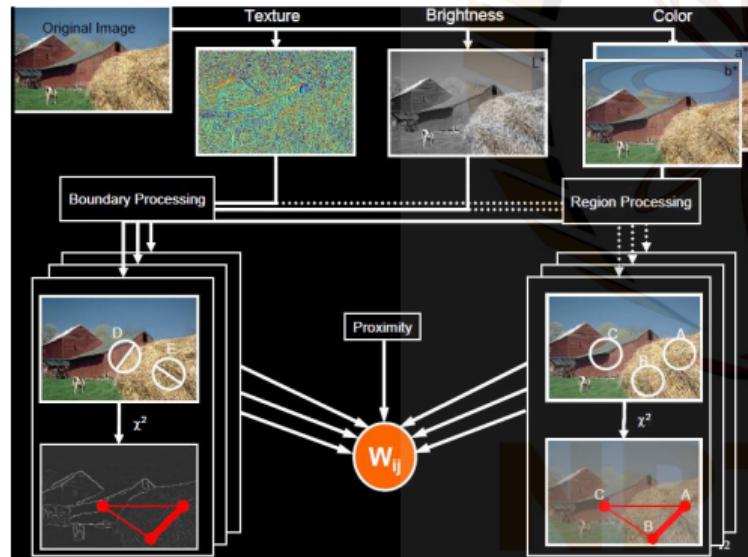
- The choice of σ (Gaussian kernel spread/size) depends on desired behavior
 - large σ detects large-scale edges
 - small σ detects fine edges



Source: S Seitz, R Urtasun

More Recent Methods in Edge Detection

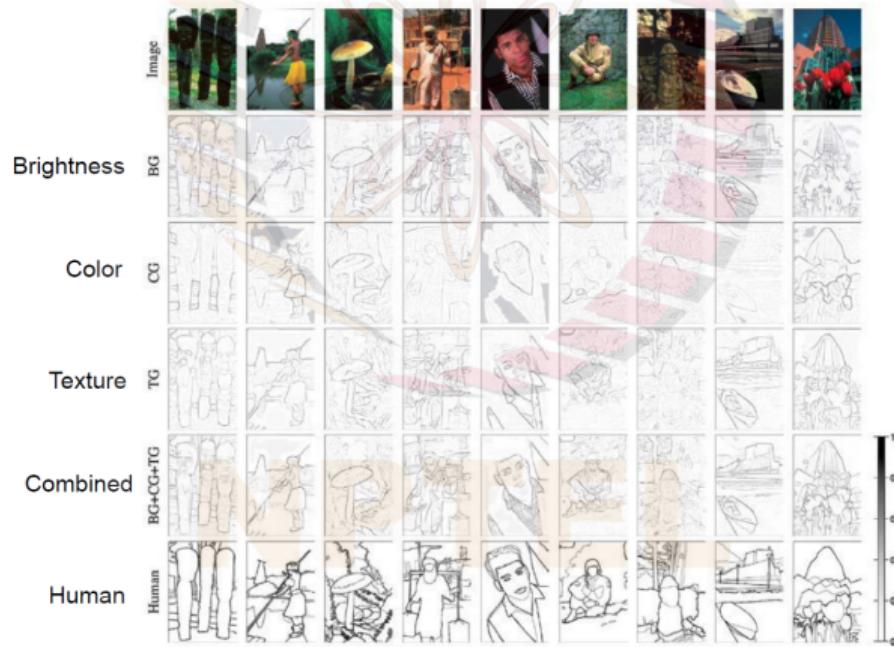
Learning to Detect Natural Image Boundaries Using Local Brightness, Color, and Texture Cues
(Martin et al, 2004)



Source: Derek Hoiem

More Recent Methods in Edge Detection

Learning to Detect Natural Image Boundaries Using Local Brightness, Color, and Texture Cues
(Martin et al, 2004)



More Recent Methods in Edge Detection

Structured Forests for Fast Edge Detection (Dollár et al, 2013)

- Goal: quickly predict whether each pixel is an edge
- Insights
 - Predictions can be learned from training data
 - Predictions for nearby pixels should not be independent
- Solution
 - Train structured random forests to split data into patches with similar boundaries based on features
 - Predict boundaries at patch level, rather than pixel level, and aggregate (average votes)



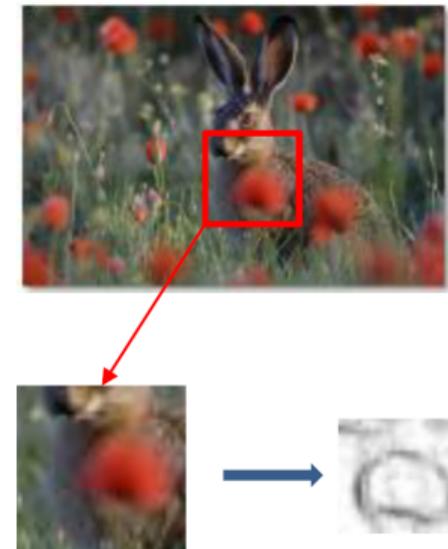
Source: Derek Hoiem

More Recent Methods in Edge Detection

Structured Forests for Fast Edge Detection (Dollár et al, 2013)

- Algorithm

- ① Extract overlapping 32×32 patches at three scales
- ② Features are pixel values and pairwise differences in feature maps (LUV color, gradient magnitude, oriented gradient)
- ③ Predict T boundary maps in the central 16×16 region using T trained decision trees
- ④ Average predictions for each pixel across all patches

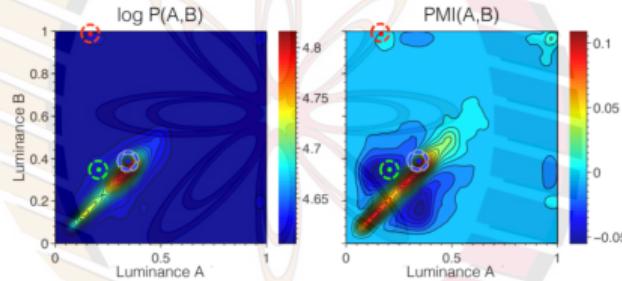


Source: Derek Hoiem

More Recent Methods in Edge Detection

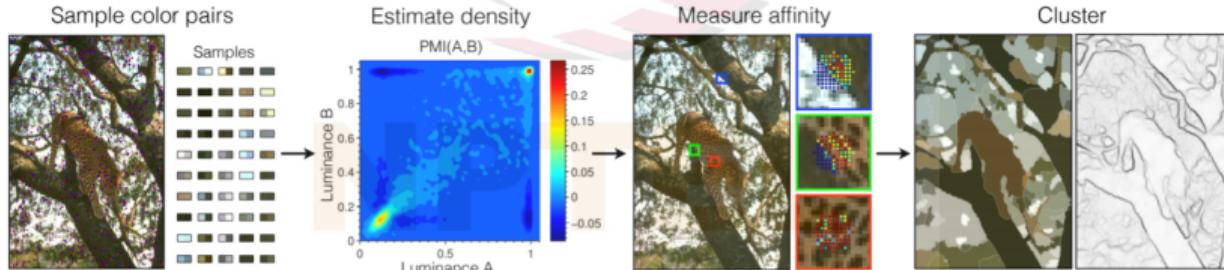
Crisp Boundary Detection using Pointwise Mutual Information (Isola et al, 2014)

- Pixel combinations that are unlikely to be together are edges



$$\text{PMI}_\rho(A, B) = \log \frac{P(A, B)^\rho}{P(A)P(B)}$$

- Algorithm Pipeline:



Source: Derek Hoiem

More Recent Methods in Edge Detection

Crisp Boundary Detection using Pointwise Mutual Information (Isola et al, 2014)



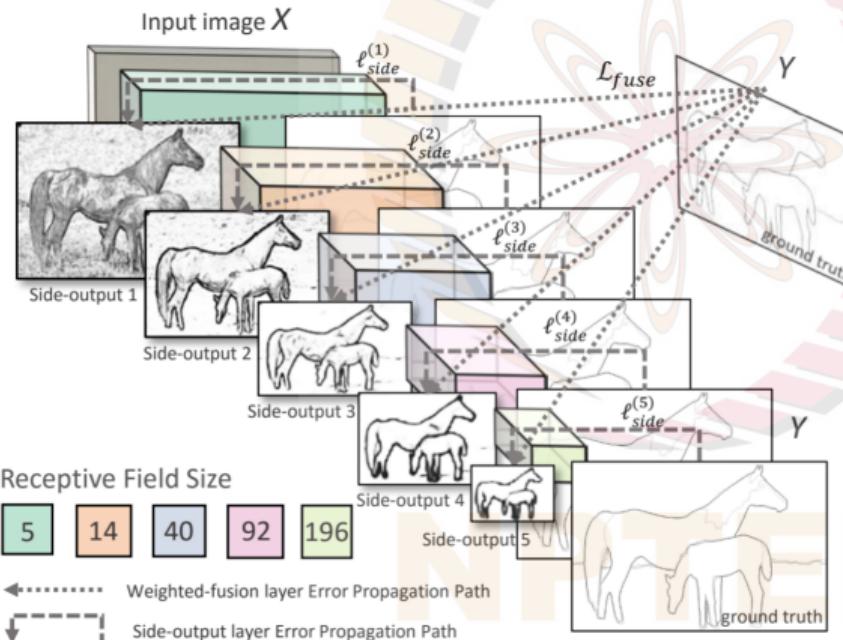
Algorithm	ODS	OIS	AP
Canny [14]	0.60	0.63	0.58
Mean Shift [36]	0.64	0.68	0.56
NCuts [37]	0.64	0.68	0.45
Felz-Hutt [38]	0.61	0.64	0.56
gPb [1]	0.71	0.74	0.65
gPb-owt-ucm [1]	0.73	0.76	0.73
SCG [9]	0.74	0.76	0.77
Sketch Tokens [7]	0.73	0.75	0.78
SE [8]	0.74	0.76	0.78
Our method – SS, color only	0.72	0.75	0.77
Our method – SS	0.73	0.76	0.79
Our method – MS	0.74	0.77	0.78

Evaluation on BSDS500

Source: Derek Hoiem

More Recent Methods in Edge Detection

Holistically Nested Edge Detection (Xie et al, 2015)



	ODS	OIS	AP	FPS
Human	.80	.80	-	-
Canny	.600	.640	.580	15
Felz-Hutt [9]	.610	.640	.560	10
BEL [5]	.660*	-	-	1/10
gPb-owt-ucm [1]	.726	.757	.696	1/240
Sketch Tokens [24]	.727	.746	.780	1
SCG [31]	.739	.758	.773	1/280
SE-Var [6]	.746	.767	.803	2.5
OEF [13]	.749	.772	.817	-
DeepNets [21]	.738	.759	.758	1/5†
N4-Fields [10]	.753	.769	.784	1/6†
DeepEdge [2]	.753	.772	.807	1/10 ³ †
CSCNN [19]	.756	.775	.798	-
DeepContour [34]	.756	.773	.797	1/30†
HED (ours)	.782	.804	.833	2.5†, 1/12

Source: Derek Hoiem

Homework

Readings

- Chapter 2, Szeliski, *Computer Vision: Algorithms and Applications*

Questions

- How do you go from Canny edges to straight lines? (*Answer in next lecture*)



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Source: Derek Hoiem

References

-  John F. Canny. "A Computational Approach to Edge Detection". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* PAMI-8 (1986), pp. 679–698.
-  David Martin, Charless Fowlkes, and Jitendra Malik. "Learning to Detect Natural Image Boundaries Using Local Brightness, Color, and Texture Cues". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 26 (June 2004), pp. 530–49.
-  Richard Szeliski. *Computer Vision: Algorithms and Applications*. Texts in Computer Science. London: Springer-Verlag, 2011.
-  Piotr Dollár and Lawrence Zitnick. "Structured Forests for Fast Edge Detection". In: *Proceedings of the International Conference on Computer Vision*. IEEE, Dec. 2013.
-  Phillip Isola et al. "Crisp Boundary Detection Using Pointwise Mutual Information". In: *Proceedings of the European Conference on Computer Vision*. 2014.
-  Saining Xie and Zhuowen Tu. "Holistically-Nested Edge Detection". In: *International Journal of Computer Vision* 125 (2015), pp. 3–18.