Deep Learning for Computer Vision

Edge Detection

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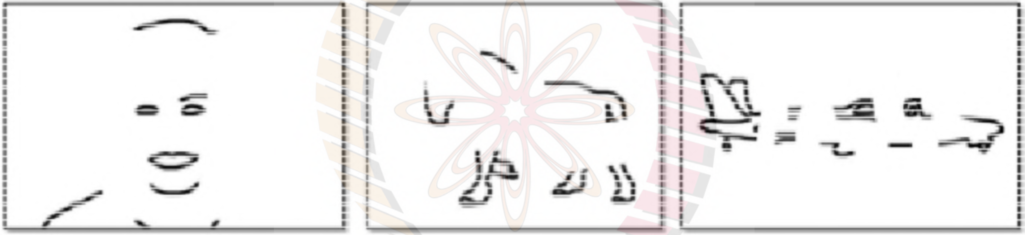
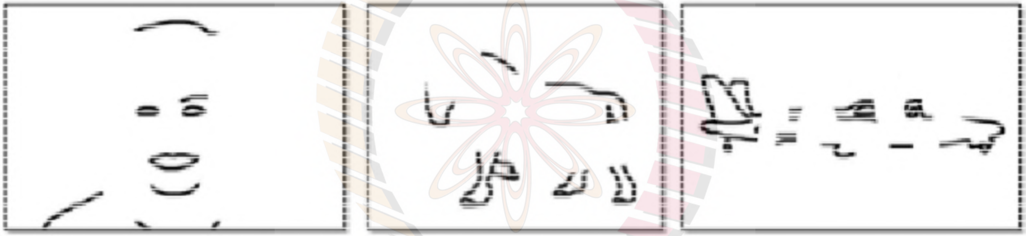
Edge Detection



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

Edge Detection



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

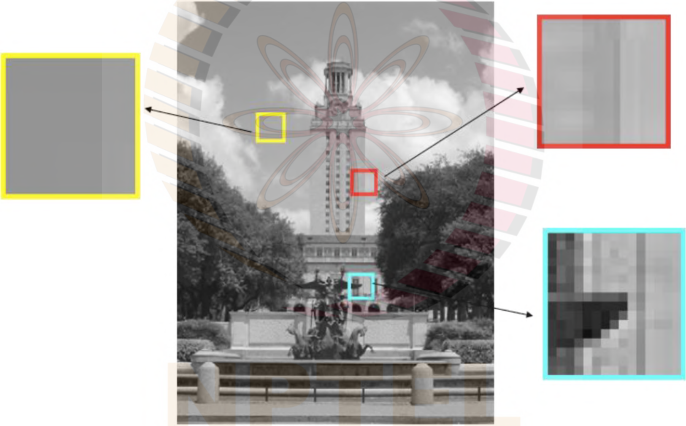
Source: Shotton, K Grauman, R Urtasun

How are Edges Caused?

- Variety of factors:

Source: R Urtasun

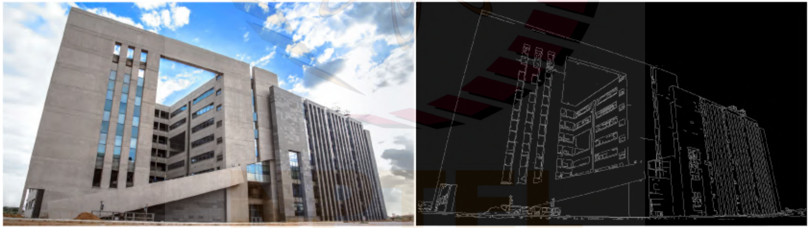
Looking More Locally



Source: K Grauman, R Urtasun

Why are Edges Important?

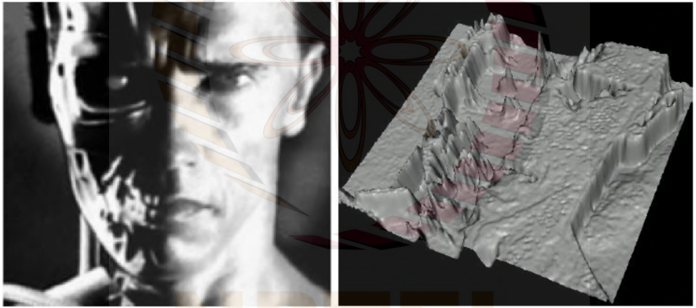
- Group pixels into objects or parts
- Allow us to track important features (e.g., corners, curves, lines).
- Cues for 3D shape
- Guiding interactive image editing



Source: Derek Hoiem

Edges in Images as Functions

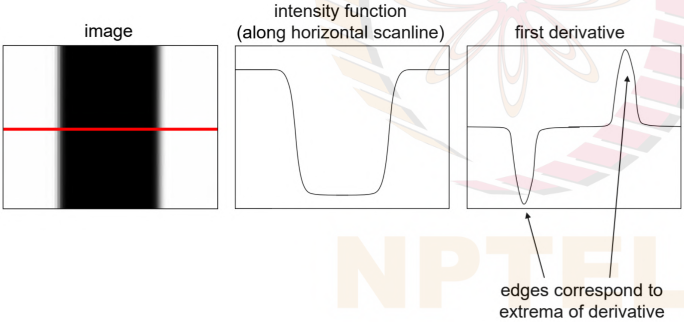
- Edges look like steep cliffs

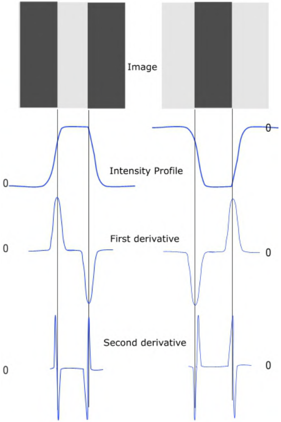


Source: N Snavely, R Urtasun

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/*](https://mipav.cit.nih.gov/)

Derivatives with Convolution

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

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

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

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

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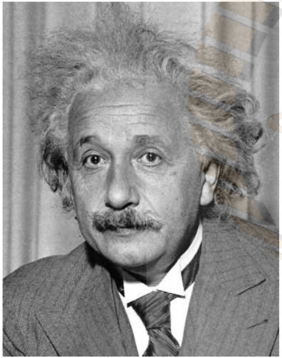
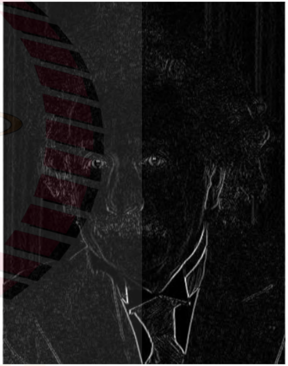
Source: K Grauman

Sobel Edge Detection Filters



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

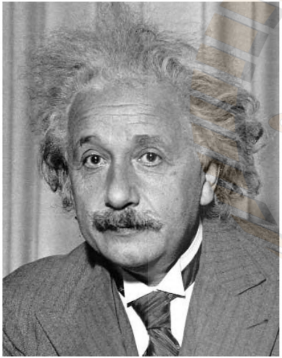
Sobel



Vertical Edge
(absolute value)

Source: J Hays

Sobel Edge Detection Filters



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

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

M_x:

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

M_y:

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

Roberts

M_x:

0	1
-1	0

M_y:

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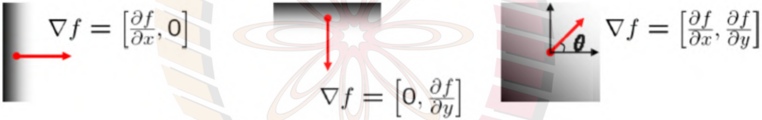
- The gradient of an image $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$
- The gradient points in the direction of most rapid change in intensity



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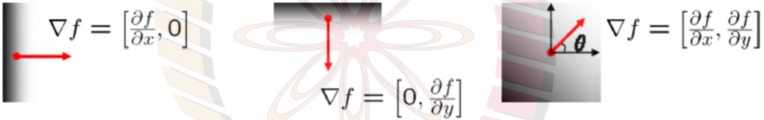

- The **gradient direction** (orientation of edge normal) is given by:

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

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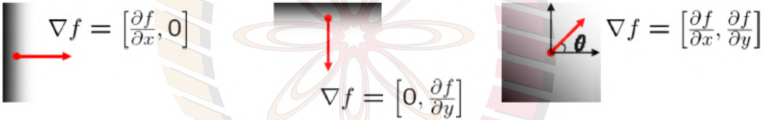


- The **gradient direction** (orientation of edge normal) is given by:

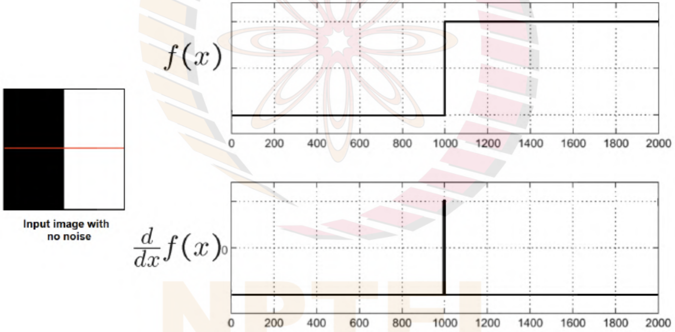
$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} \Big/ \frac{\partial f}{\partial x}\right)$$

- 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

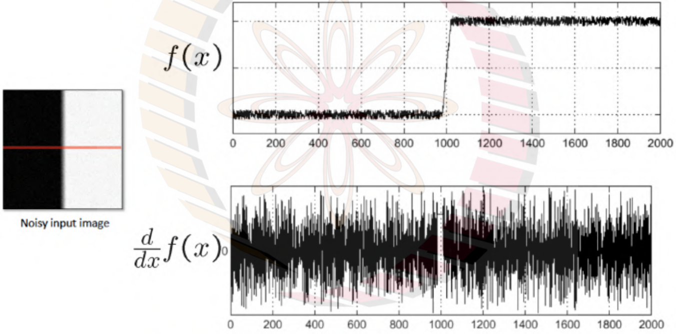
Derivative with No Noise

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



Where is the edge?

Effect of Noise

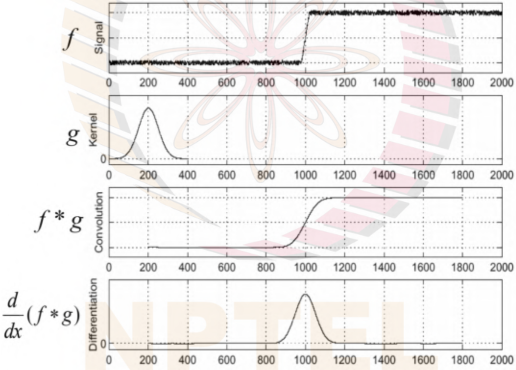


Now, where is the edge?

Source: S Seitz, K Grauman

Effect of Noise

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



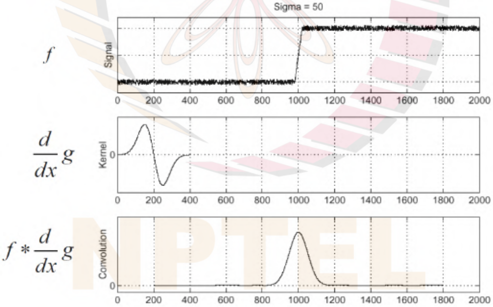
Source: S Seitz, R Urtasun

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

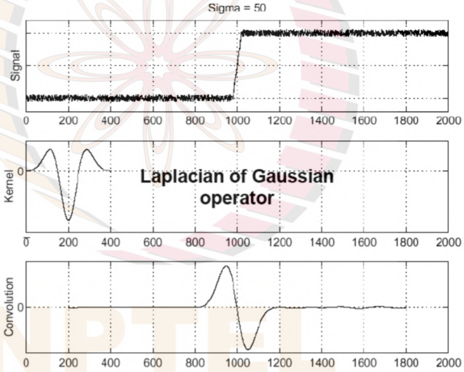
What about Second Derivative?

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

f

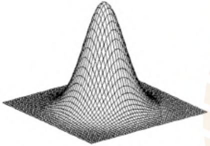
$\frac{\partial^2}{\partial x^2}h$

$(\frac{\partial^2}{\partial x^2}h) \star f$



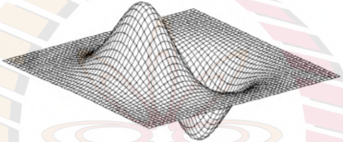
Source: S Seitz, R Urtasun

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)

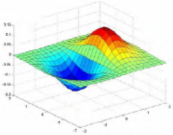
$\frac{\partial}{\partial x} h_\sigma(u,v)$

Laplacian of Gaussian

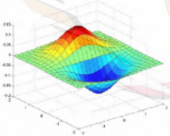
$\nabla^2 h_\sigma(u,v)$

with ∇^2 the Laplacian operator

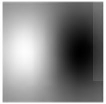
$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$



x-direction



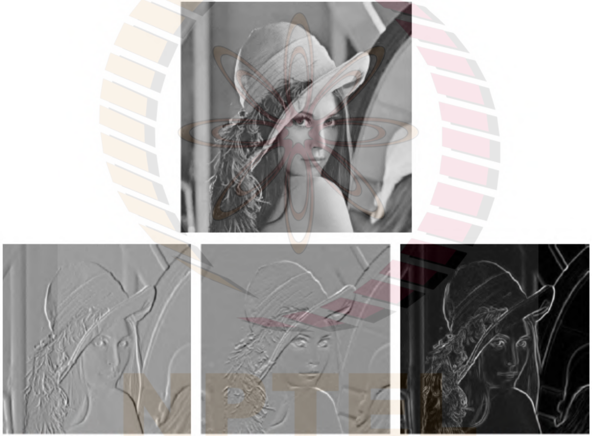
y-direction



Which one finds horizontal/vertical edges?

Source: S Seitz, R Urtasun

Compute of Gradients



Source: S Seitz, R Urtasun

Properties of an Edge Detector

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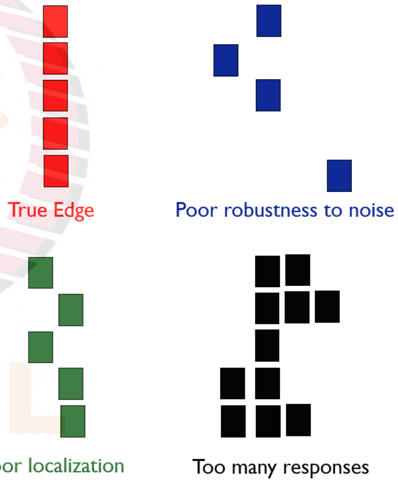
- Criteria for a good edge detector?

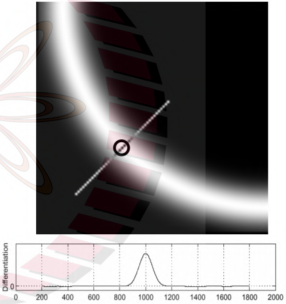
Properties of an Edge Detector

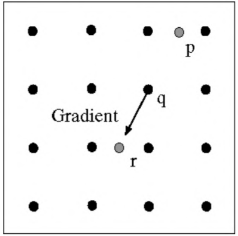
- Criteria for a good edge detector?
  - **Good detection:** find all real edges, ignoring noise or other artifacts
  - **Good localization:** detect edges as close as possible to true edges
  - **Single response:** return one point only for each true edge point



Source: K Grauman

Non-Maxima Suppression

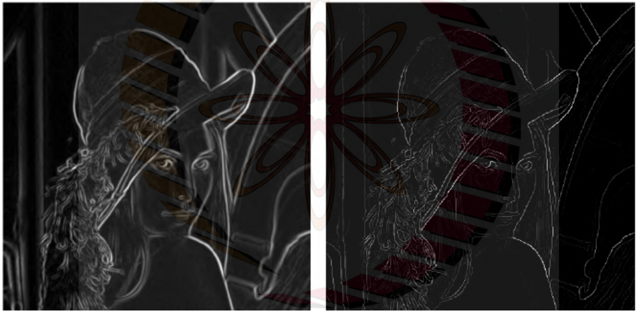




- Check if pixel is local maximum along gradient direction:
  - Could require checking interpolated pixels p and r

Source: N Snavely, R Urtasun

Non-Maxima Suppression



Before and after non-maxima suppression

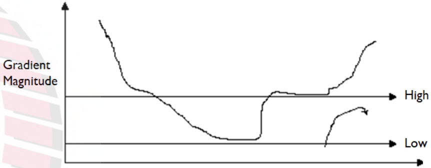
Source: Derek Hoiem

Hysteresis Thresholding

- Check for well-connected edges. How?

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' $\implies$ **'edge pixel'**
  - If gradient at pixel $<$ 'Low' $\implies$ **'non-edge pixel'**
  - If gradient at pixel $\geq$ 'Low' and $\leq$ 'High' $\implies$ **'edge pixel'** iff it is connected to an 'edge pixel' directly or via pixels between 'Low' and 'High'



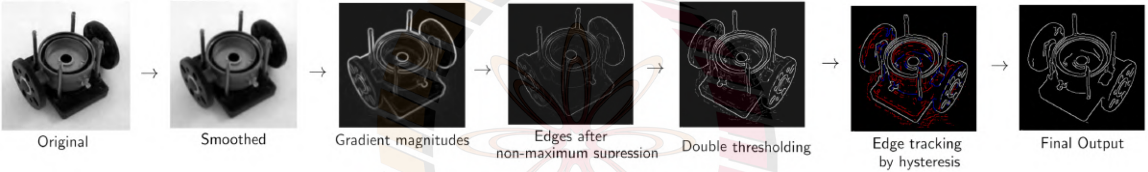
Source: S Seitz, R Urtasun

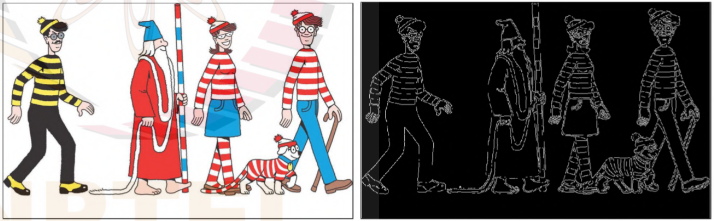
Canny Edge Detector

- 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

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

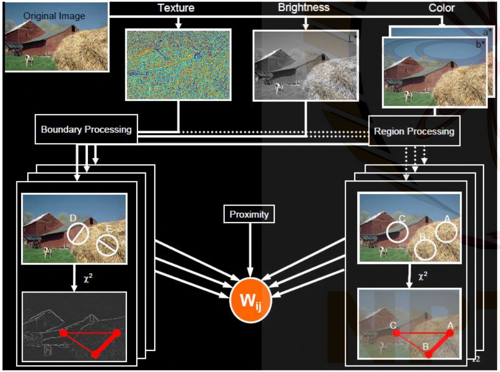
- The choice of σ (Gaussian kernel spread/size) depends on desired behavior
  - large σ detects large-scale edges
  - small σ detects fine edges

original | Canny with $\sigma = 1$ | Canny with $\sigma = 2$

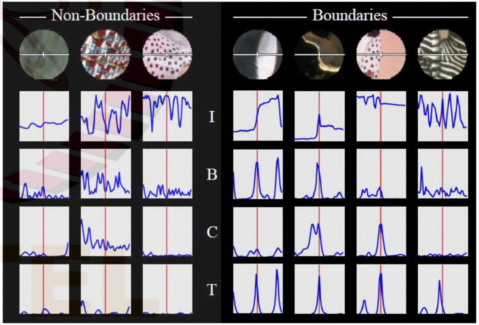
Source: S Seitz, R Urtasun

More Recent Methods in Edge Detection

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



pB Boundary Detector



Source: Derek Hoiem

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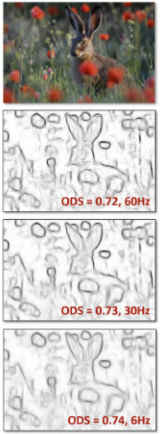
More Recent Methods in Edge Detection

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)

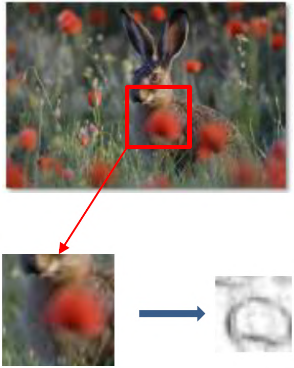


Source: Derek Hoiem

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

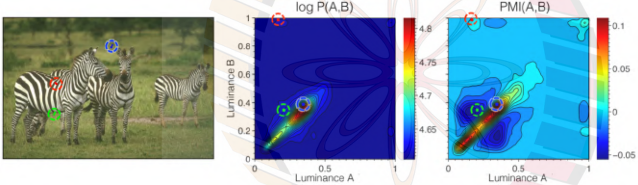


Source: Derek Hoiem

More Recent Methods in Edge Detection

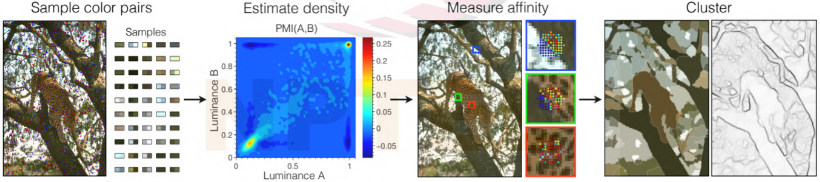
Crisp Boundary Detection using Pointwise Mutual Information (Isola et al, 2014)

- Pixel combinations that are unlikely to be together are edges



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

- Algorithm Pipeline:



Source: Derek Hoiem

More Recent Methods in Edge Detection

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

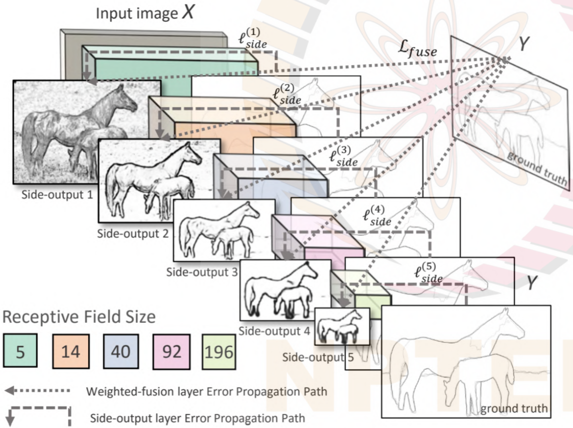
Algorithm	ODS	OIS	AP
Canny [14]	0.60	0.63	0.58
Mean Shift [36]	0.64	0.68	0.56
NCuts [37]	0.64	0.68	0.45
Felz-Hutt [38]	0.61	0.64	0.56
gPb [1]	0.71	0.74	0.65
gPb-owt-ucm [1]	0.73	0.76	0.73
SCG [9]	**0.74**	0.76	0.77
Sketch Tokens [7]	0.73	0.75	0.78
SE [8]	**0.74**	0.76	0.78
Our method – SS, color only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

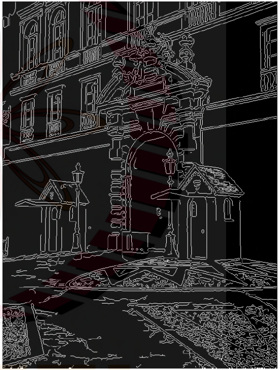
Homework

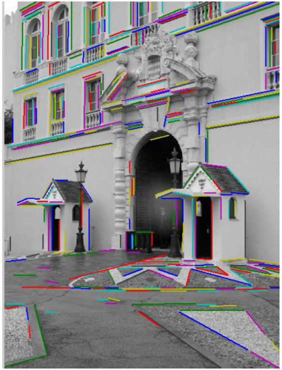
Readings

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

Questions

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





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.
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- 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.