南京大学
NANJING UNIVERSITY

计算机视觉表征与识别
Chapter 5: Edges

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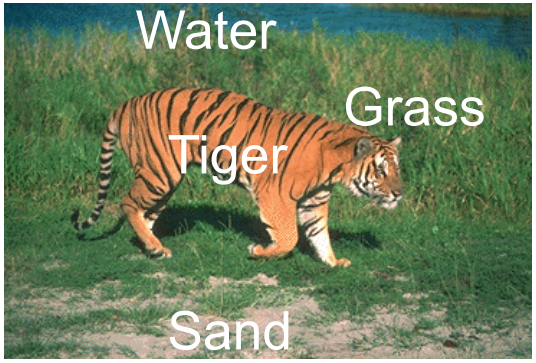
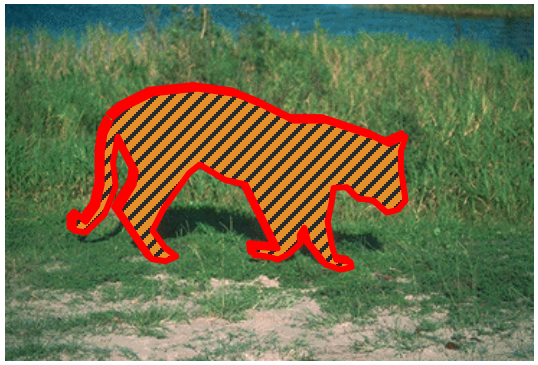
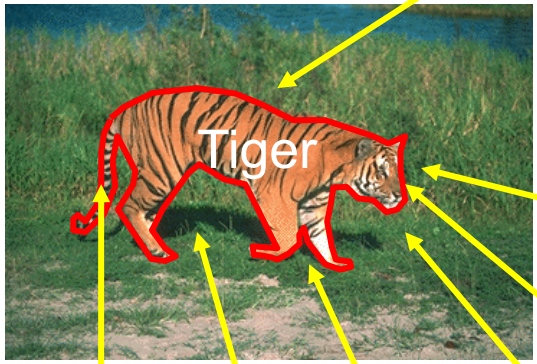
Today's class

- Introduction to edge detection.
- Gradients and edges.
- Canny edge detector.
- Object contour.
- Pb edge detector.
- Recent advances in edge detection.
- Straight line detection

From Pixels to Perception





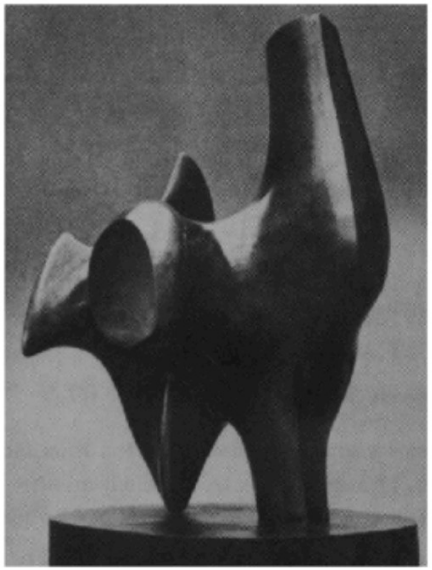


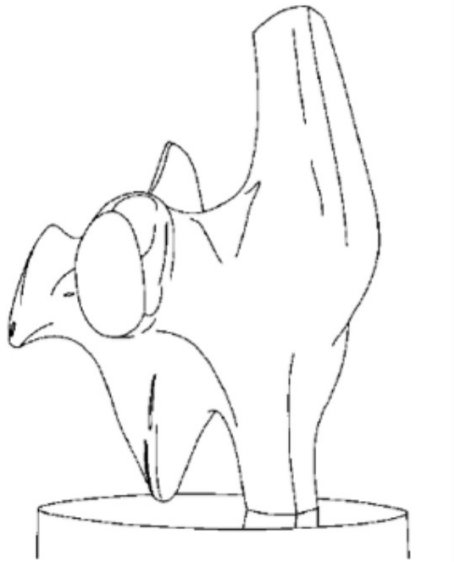
back
head
eye
mouth
legs
tail
shadow

Mid-level operations of Segmentation and Grouping

First problem: edge detection

- Goal: compute something like a line drawing of a scene





Issues

- No precise problem formulation
- Much harder than it seems to be
- Edge detectors usually work by detecting “big changes” in image intensity
- Boundary is contour in the image plane that represents a change in pixel ownership from object or surface to another.

Edge detection

- **Goal**: map image from 2d array of pixels to a set of curves or line segments or contours.

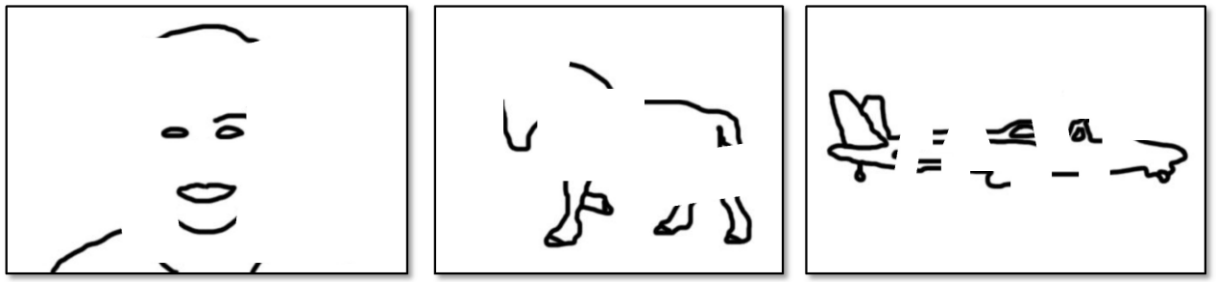
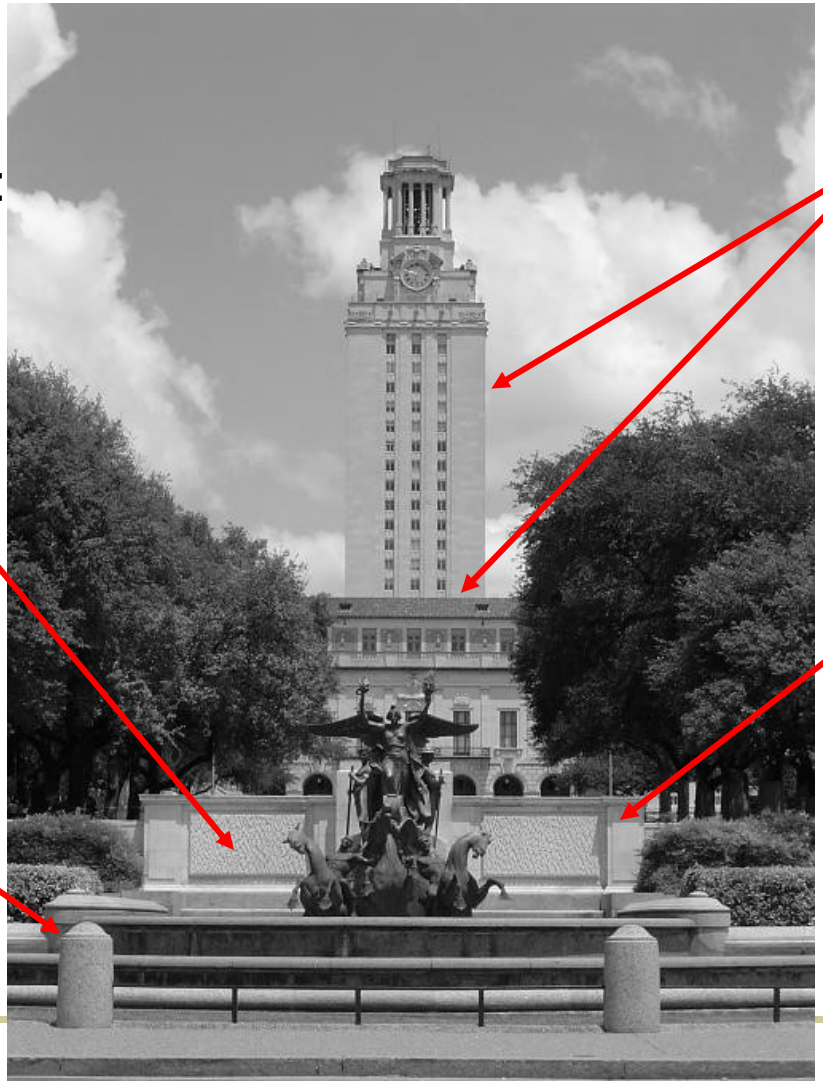


Figure from J. Shotton et al., PAMI 2007

- **Main idea**: look for strong gradients, post-process

What causes an edge?



Reflectance change: appearance information, texture

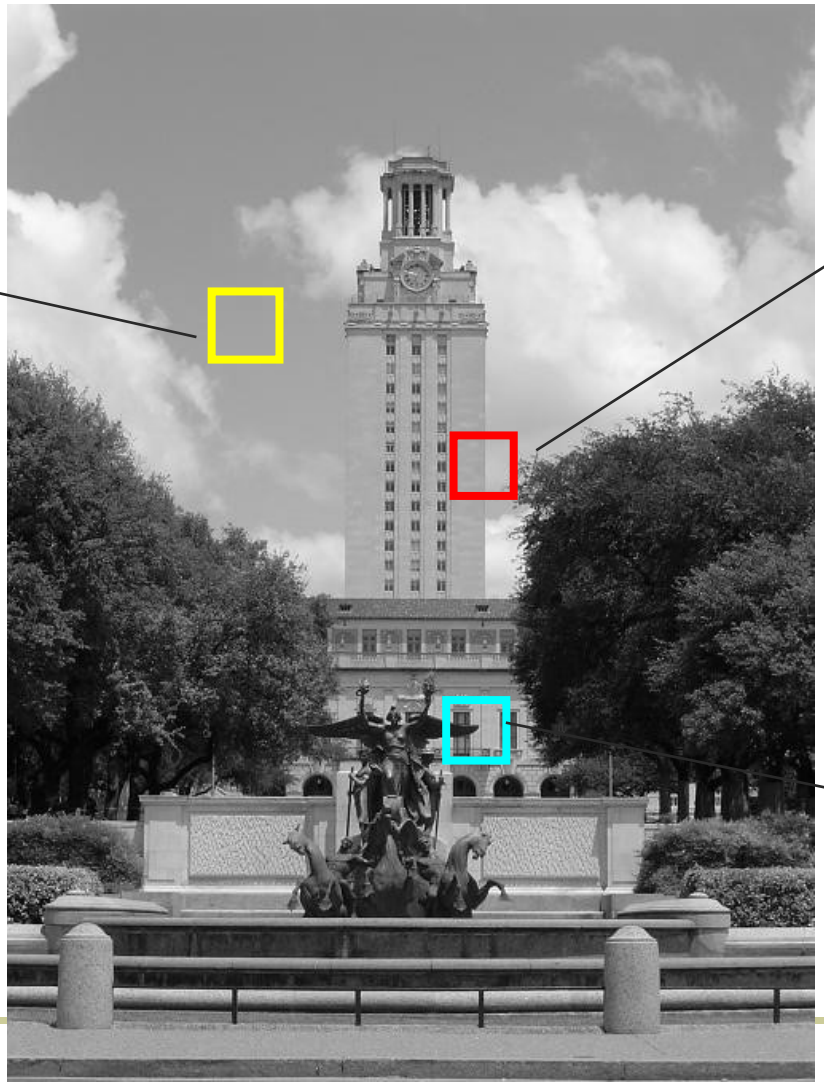
Depth discontinuity: object boundary

Cast shadows

Change in surface orientation: shape

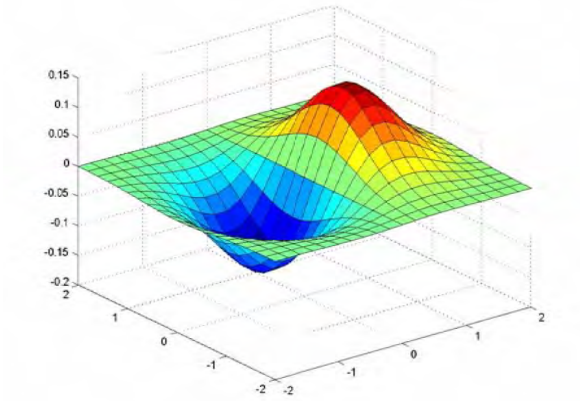
Slide credit: Kristen Grauman

Edges/gradients and invariance

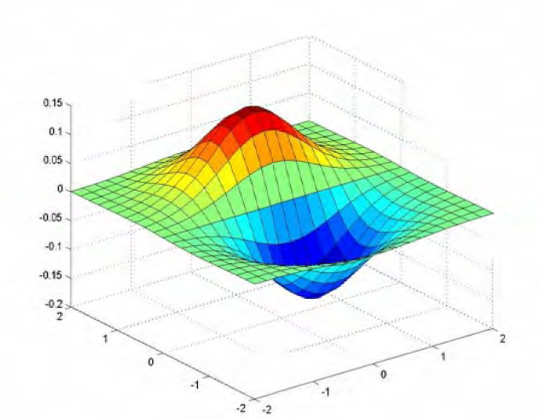


Slide credit:
Kristen Grauman

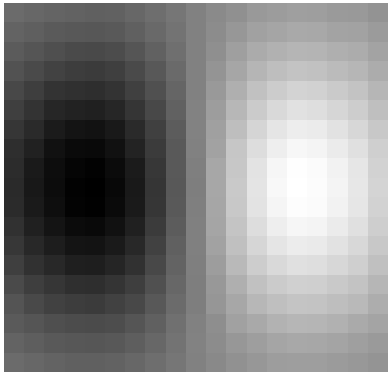
Derivative of Gaussian filters

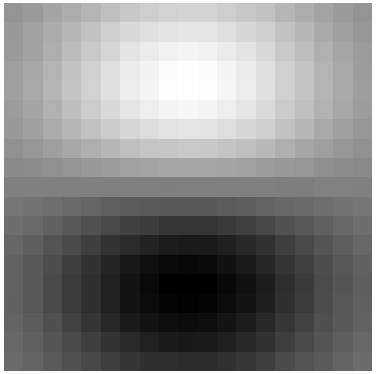


***x*-direction**



***y*-direction**





Source: L. Lazebnik

The Sobel Operator: A common approximation of derivative of gaussian

- Common approximation of derivative of Gaussian

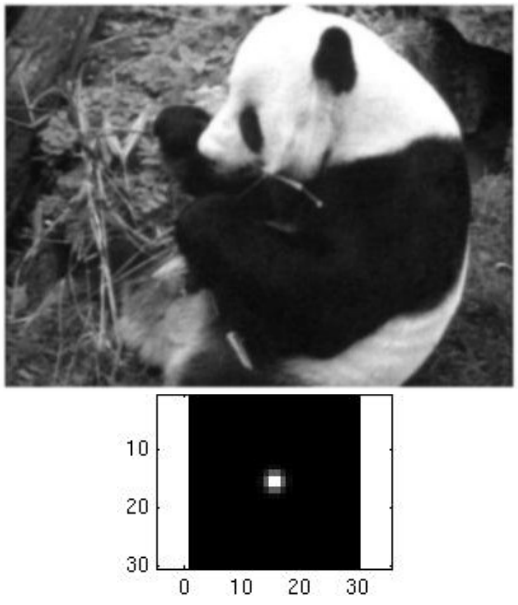
$$\frac{1}{8}\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad s_x$$

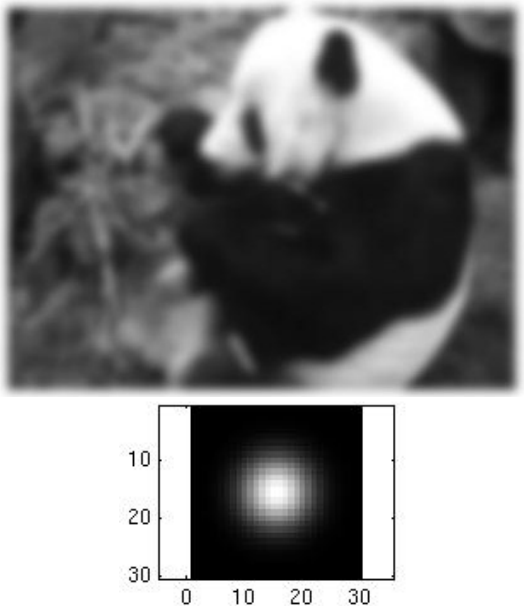
$$\frac{1}{8}\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \qquad s_y$$

- The standard defn. of the Sobel operator omits the 1/8 term
  - doesn't make a difference for edge detection
  - the 1/8 term **is** needed to get the right gradient value

Smoothing with a Gaussian

Recall: parameter σ is the “scale” / “width” / “spread” of the Gaussian kernel, and controls the amount of smoothing.





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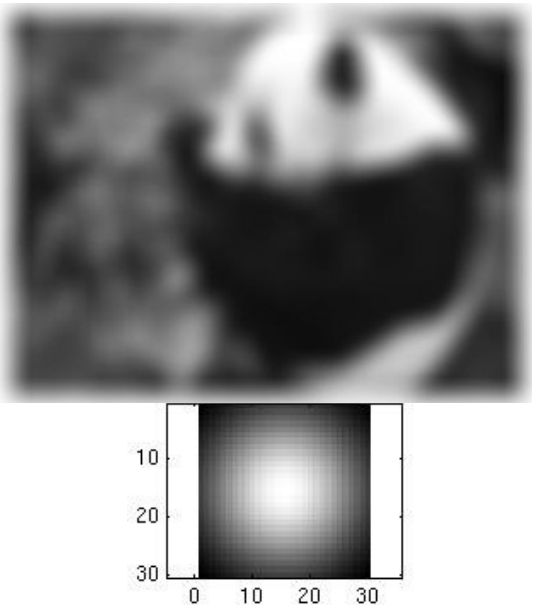
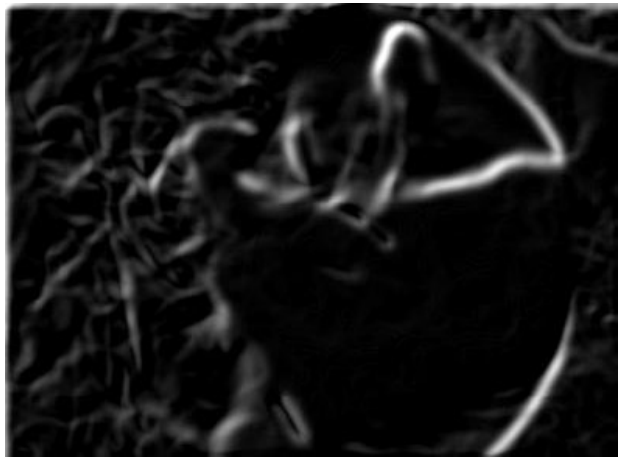


Effect of σ on derivatives

σ = 1 pixel



σ = 3 pixels

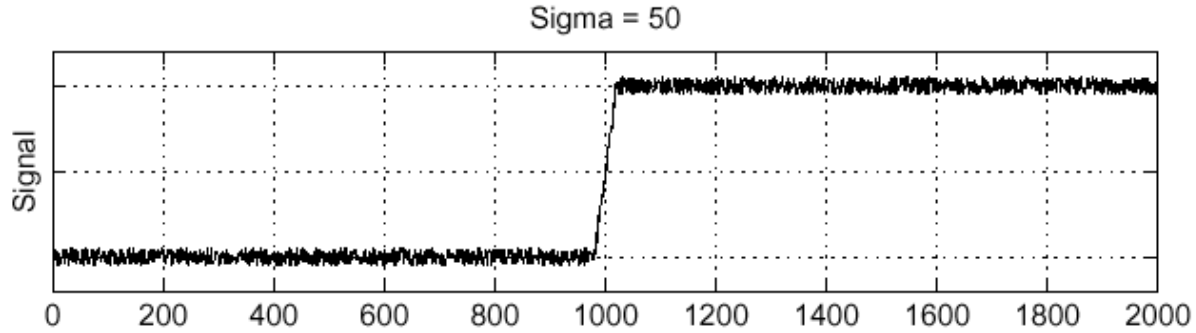
The apparent structures differ depending on Gaussian's scale parameter.
Larger values: larger scale edges detected
Smaller values: finer features detected

Slide credit: Kristen Grauman

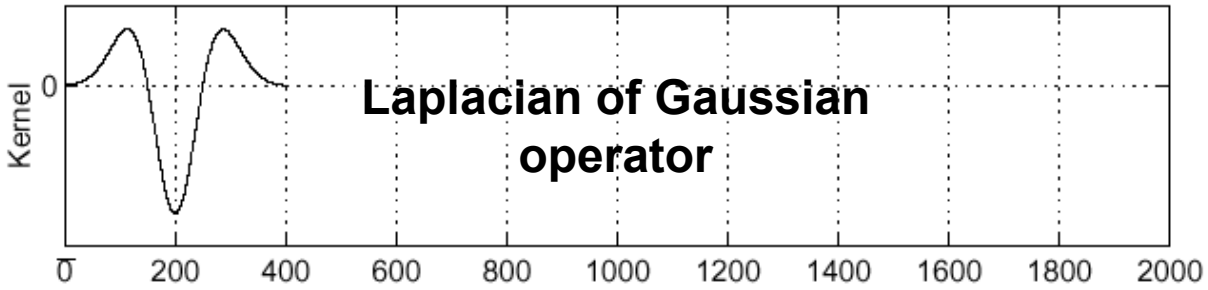
Laplacian of Gaussian

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

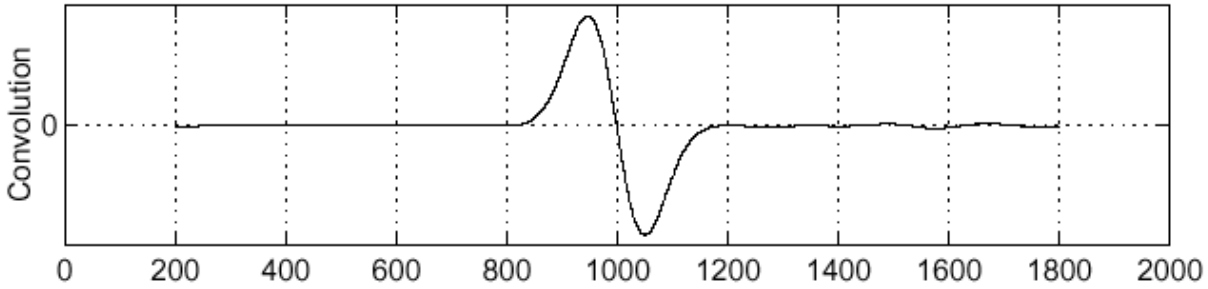
f



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



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

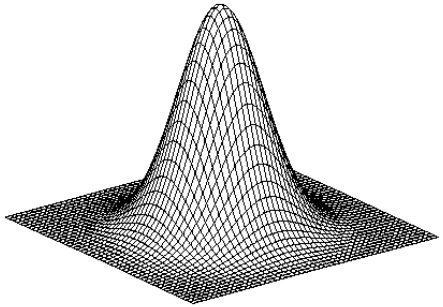


Where is the edge?

Zero-crossings of bottom graph

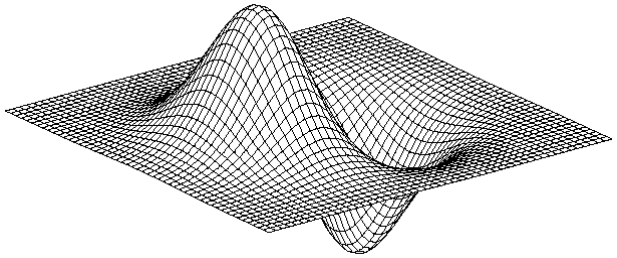
Slide credit: Steve S

2D edge detection filters



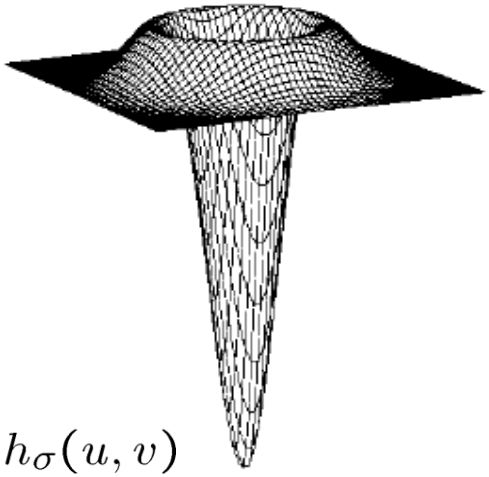
Gaussian

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



derivative of Gaussian

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



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

Laplacian of Gaussian

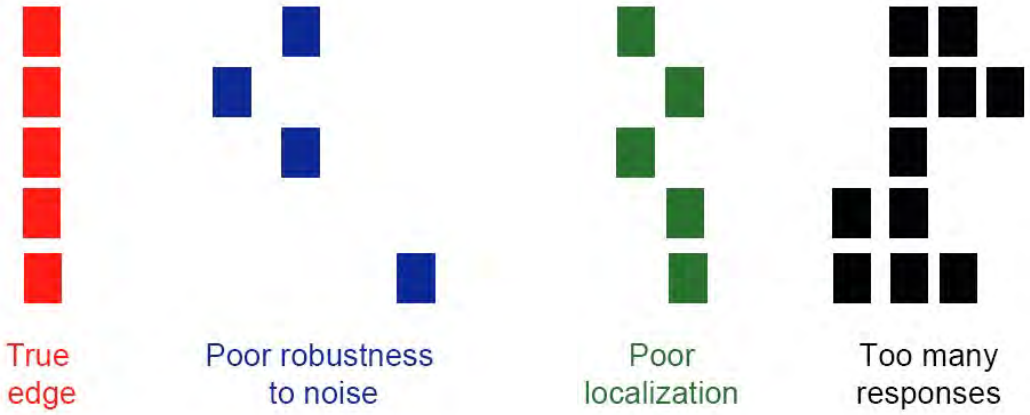
- ∇^2 is the Laplacian operator:

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

Slide credit: Steve Seitz

Designing an edge detector

- Criteria for an “optimal” edge detector:
  - **Good detection:** minimize the probability of false positives (detecting spurious edges caused by noise), as well as that of false negatives (missing real edges)
  - **Good localization:** must be as close as possible to the true edges
  - **Single response:** the detector must return one point only for each true edge point;



Basic Comparisons of Edge Operators

Gradient:

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

Good Localization
Noise Sensitive
Poor Detection

Roberts (2 x 2):

0	1
-1	0

1	0
0	-1

Sobel (3 x 3):

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

1	1	1
0	0	0
-1	-1	1

Sobel (5 x 5):

-1	-2	0	2	1
-2	-3	0	3	2
-3	-5	0	5	3
-2	-3	0	3	2
-1	-2	0	2	1

1	2	3	2	1
2	3	5	3	2
0	0	0	0	0
-2	-3	-5	-3	-2
-1	-2	-3	-2	-1

Poor Localization
Less Noise Sensitive
Good Detection

Gradients -> edges

Primary edge detection steps:

1. Smoothing: suppress noise
2. Edge enhancement: filter for contrast
3. Edge localization

   Determine which local maxima from filter output are actually edges vs. noise

   Thresholding and thinning

Example: Laplacian of Gaussian (LoG) and Canny Edge Detector

Marr and Hildreth Filtering, 1980.

- Smooth Image with Gaussian Filter
- Applying the Laplacian for a Gaussian-filtered image can be done in one step of convolution.
- Find zero-crossings
- Find slope of zero-crossings
- Apply threshold to slope and mark edges

J. Canny. 1986

- Smooth Image with Gaussian filter
- Compute Derivative of filtered image
- Find Magnitude and Orientation of gradient
- Apply Non-max suppression
- Apply Thresholding (Hysteresis)

Canny edge detector

- This is probably the most widely used edge detector in computer vision
- Theoretical model: step-edges corrupted by additive Gaussian noise
- Canny has shown that the first derivative of the Gaussian closely approximates the operator that optimizes the product of *signal-to-noise ratio* and localization

J. Canny, ***A Computational Approach To Edge Detection***, IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679-714, 1986.

Canny edge detector

- Filter image with derivative of Gaussian
- Find magnitude and orientation of gradient
- **Non-maximum suppression**:
  - Thin wide “ridges” down to single pixel width
- **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
- MATLAB: `edge(image, 'canny');`
- `>>help edge`

Source: D. Lowe, L. Fei-Fei

The Canny edge detector

original image (Lena)

Slide credit: Steve S

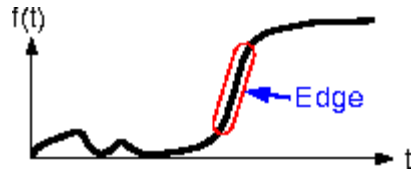
The Canny edge detector

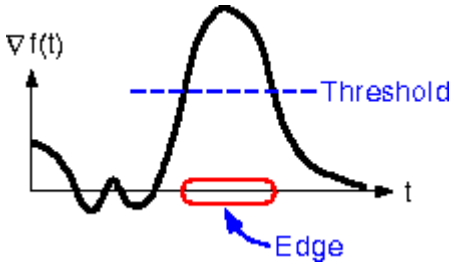
norm of the gradient

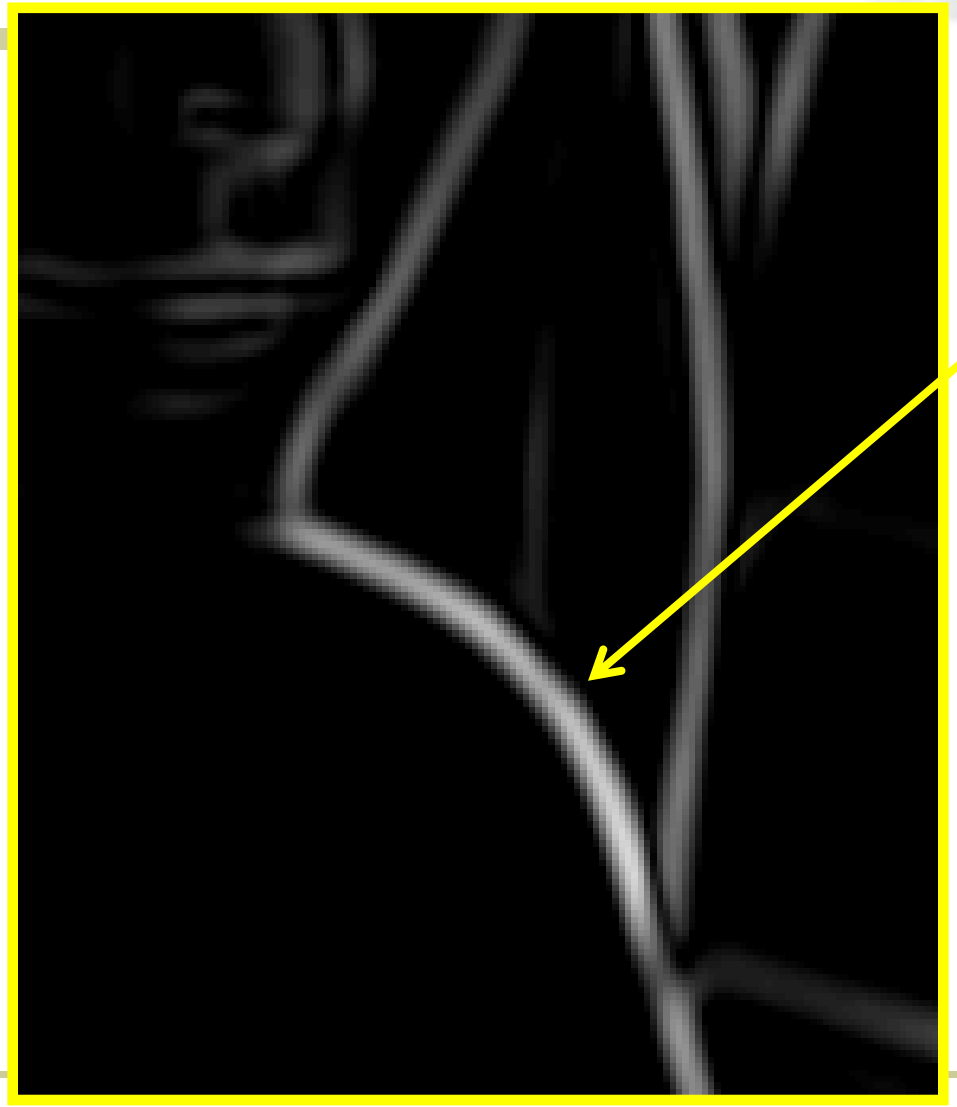
The Canny edge detector

thresholding

The Canny edge detector

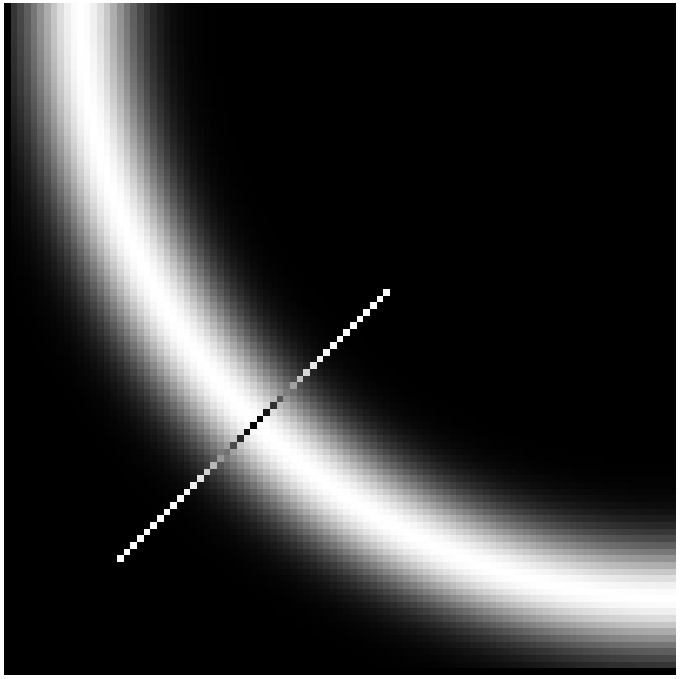


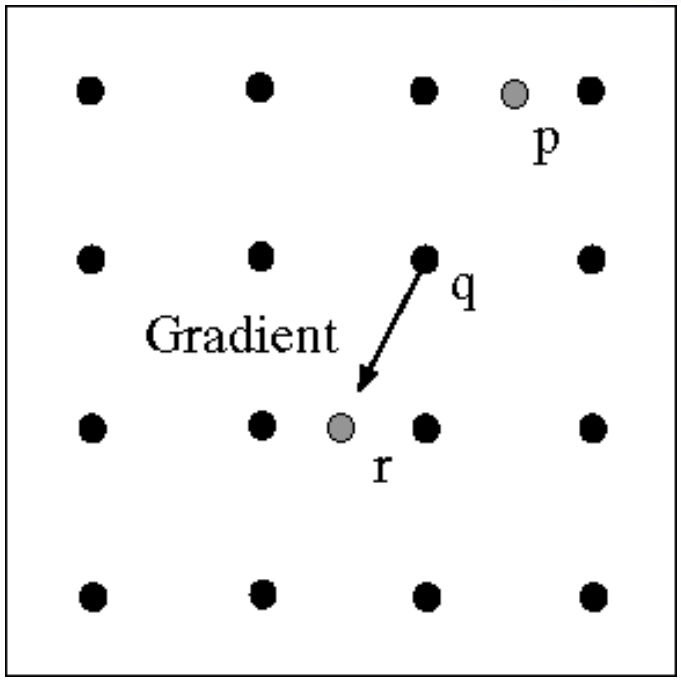




How to turn these thick regions of the gradient into curves?

Non-maximum suppression



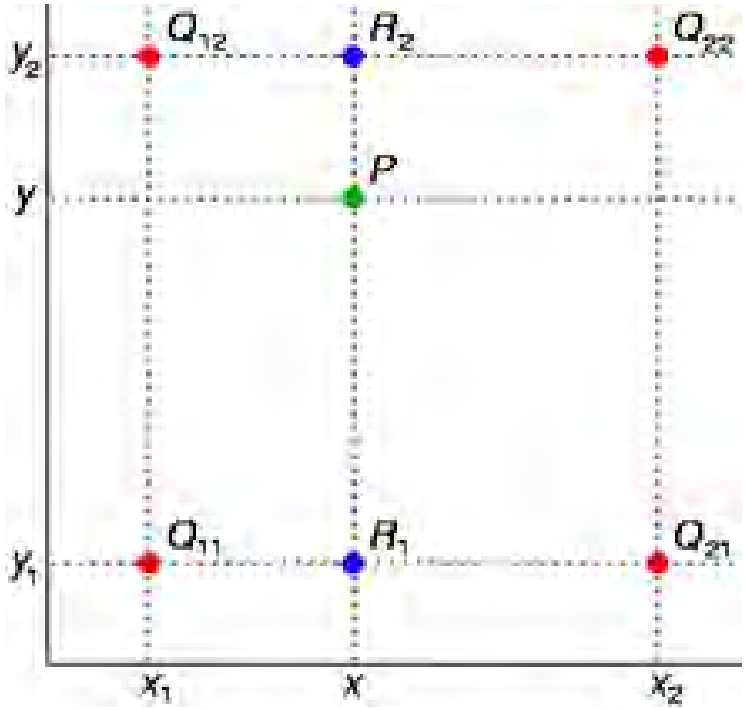


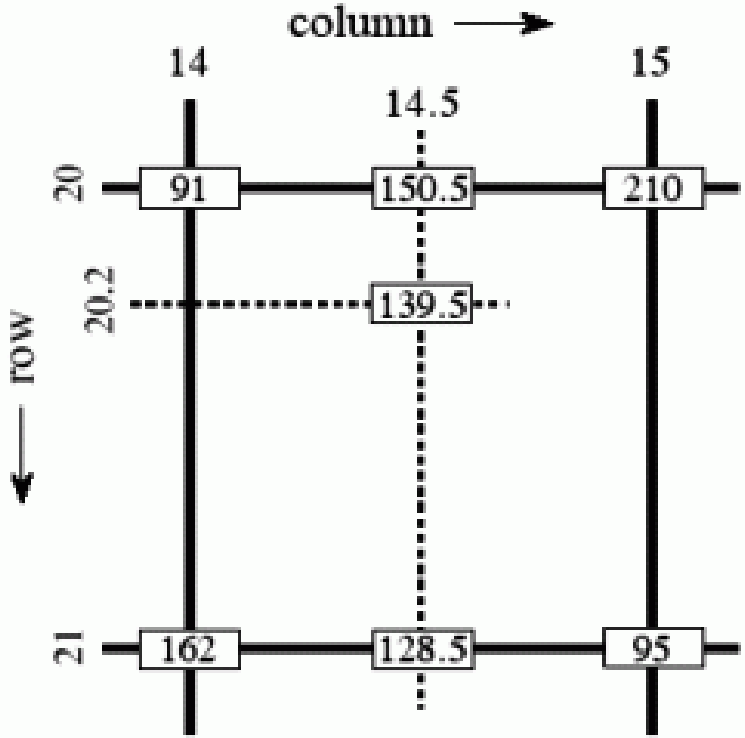
Check if pixel is local maximum along gradient direction, select single max across width of the edge

- requires checking interpolated pixels p and r

Bilinear Interpolation

$$f(x,y) \approx \begin{bmatrix} 1-x & x \end{bmatrix} \begin{bmatrix} f(0,0) & f(0,1) \\ f(1,0) & f(1,1) \end{bmatrix} \begin{bmatrix} 1-y \\ y \end{bmatrix}.$$

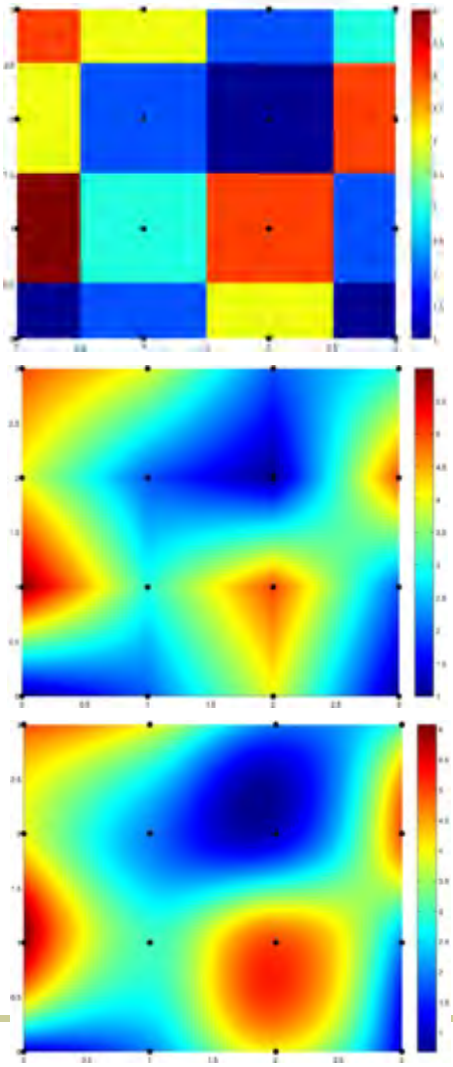




http://en.wikipedia.org/wiki/Bilinear_interpolation

Sidebar: Interpolation options

- imx2 = imresize(im, 2, interpolation_type)
- ‘nearest’
  - Copy value from nearest known
  - Very fast but creates blocky edges
- ‘bilinear’
  - Weighted average from four nearest known pixels
  - Fast and reasonable results
- ‘bicubic’ (default)
  - Non-linear smoothing over larger area
  - Slower, visually appealing, may create negative pixel values



Examples from http://en.wikipedia.org/wiki/Bicubic_interpolation

Before non-max suppression

After non-max suppression

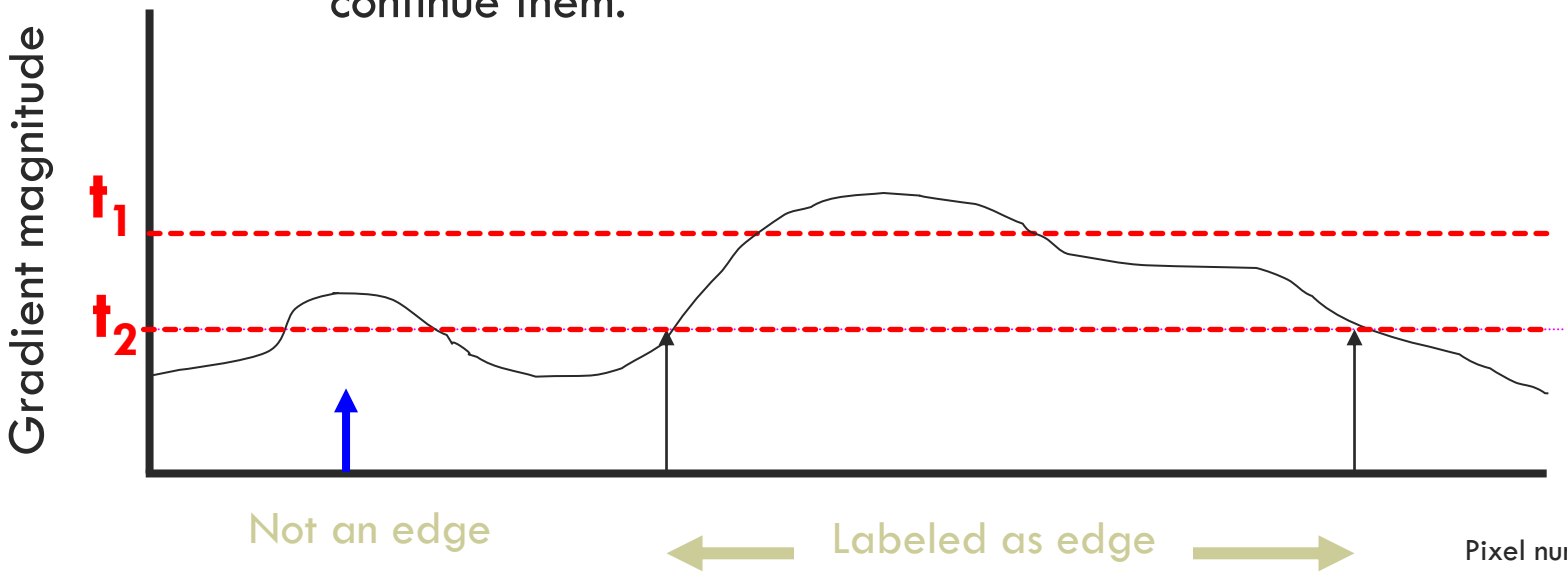
Problem: pixels along this edge didn't survive the thresholding

Hysteresis thresholding

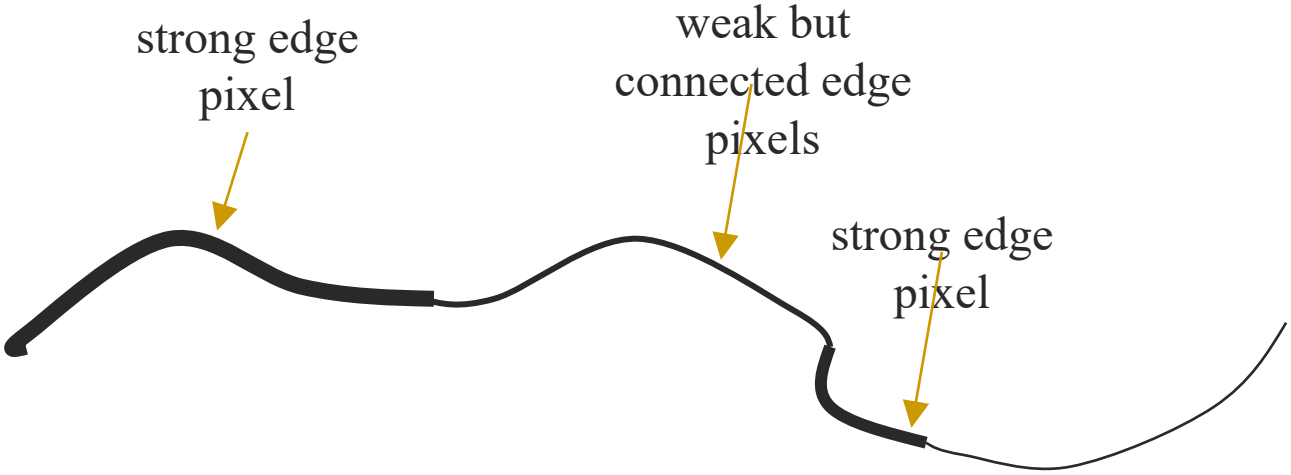
- Threshold at low/high levels to get weak/strong edge pixels
- Do connected components, starting from strong edge pixels

Closing edge gaps

- Check that maximum value of gradient value is sufficiently large
  - drop-outs? use **hysteresis**
    - use a high threshold to start edge curves and a low threshold to continue them.



Hysteresis thresholding



Source: S. Seitz

Hysteresis thresholding

original image

high threshold (strong edges)

low threshold (weak edges)

hysteresis threshold

Final Canny Edges

Effect of σ (Gaussian kernel spread/size)

original

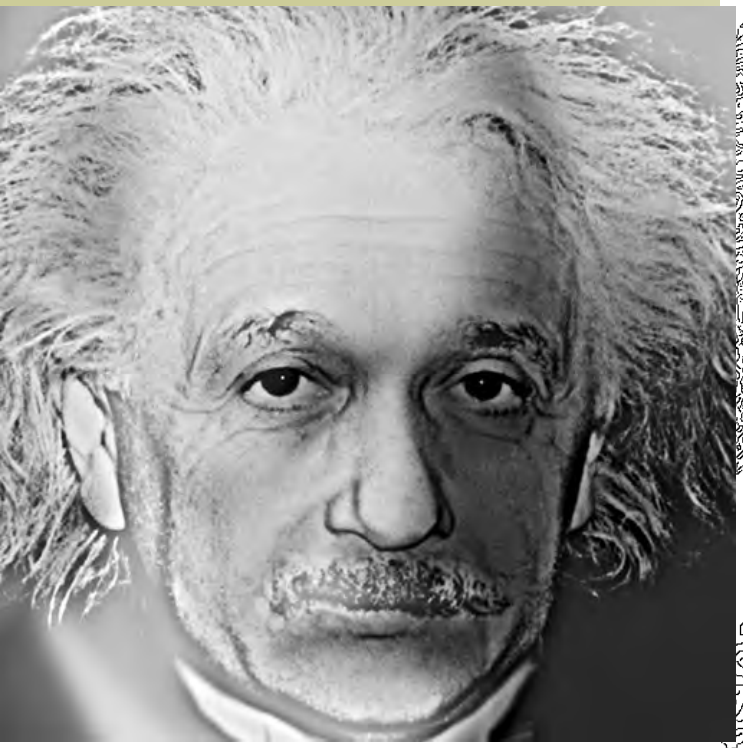
Canny with $\sigma = 1$

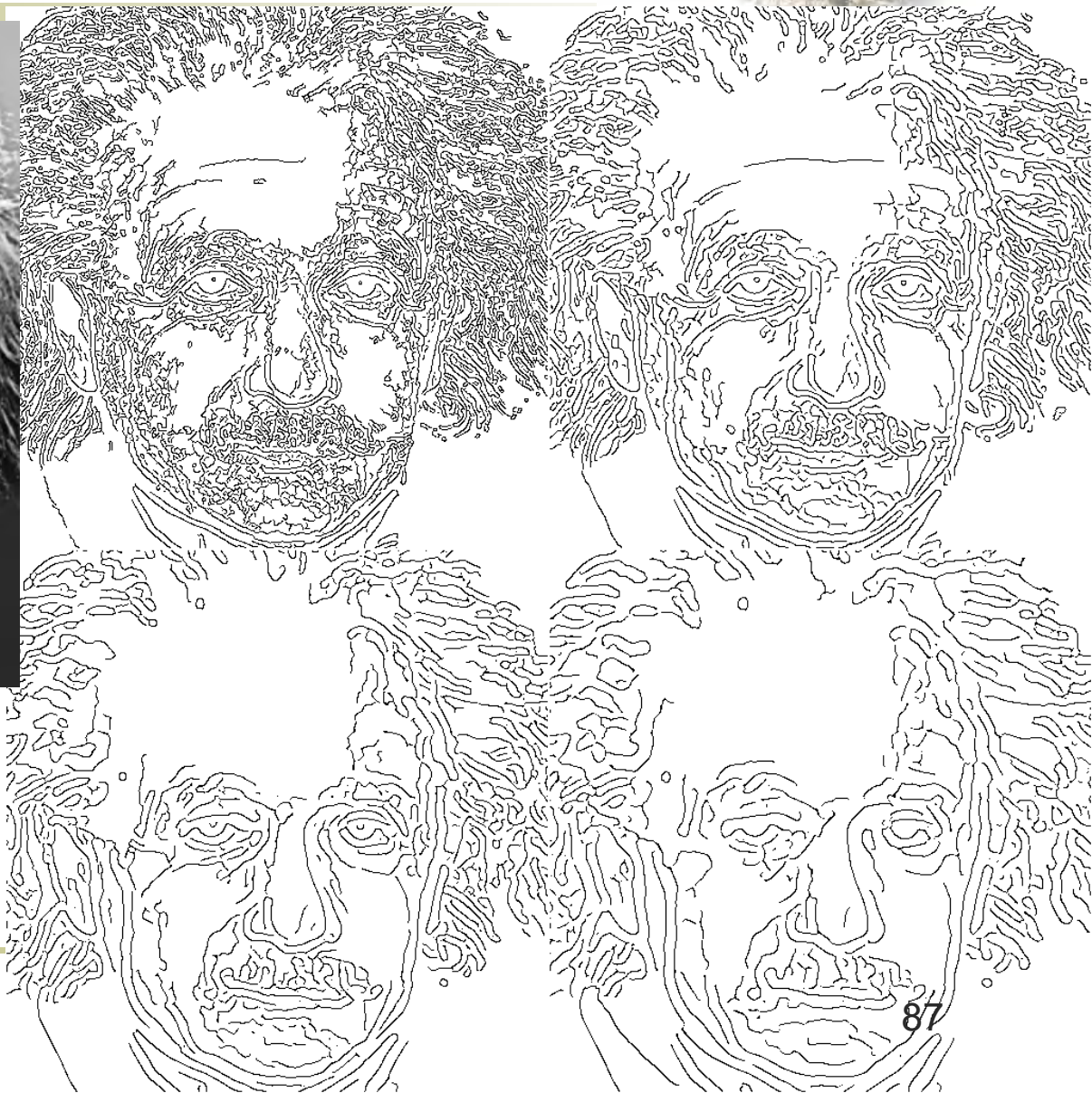
Canny with $\sigma = 2$

The choice of σ depends on desired behavior

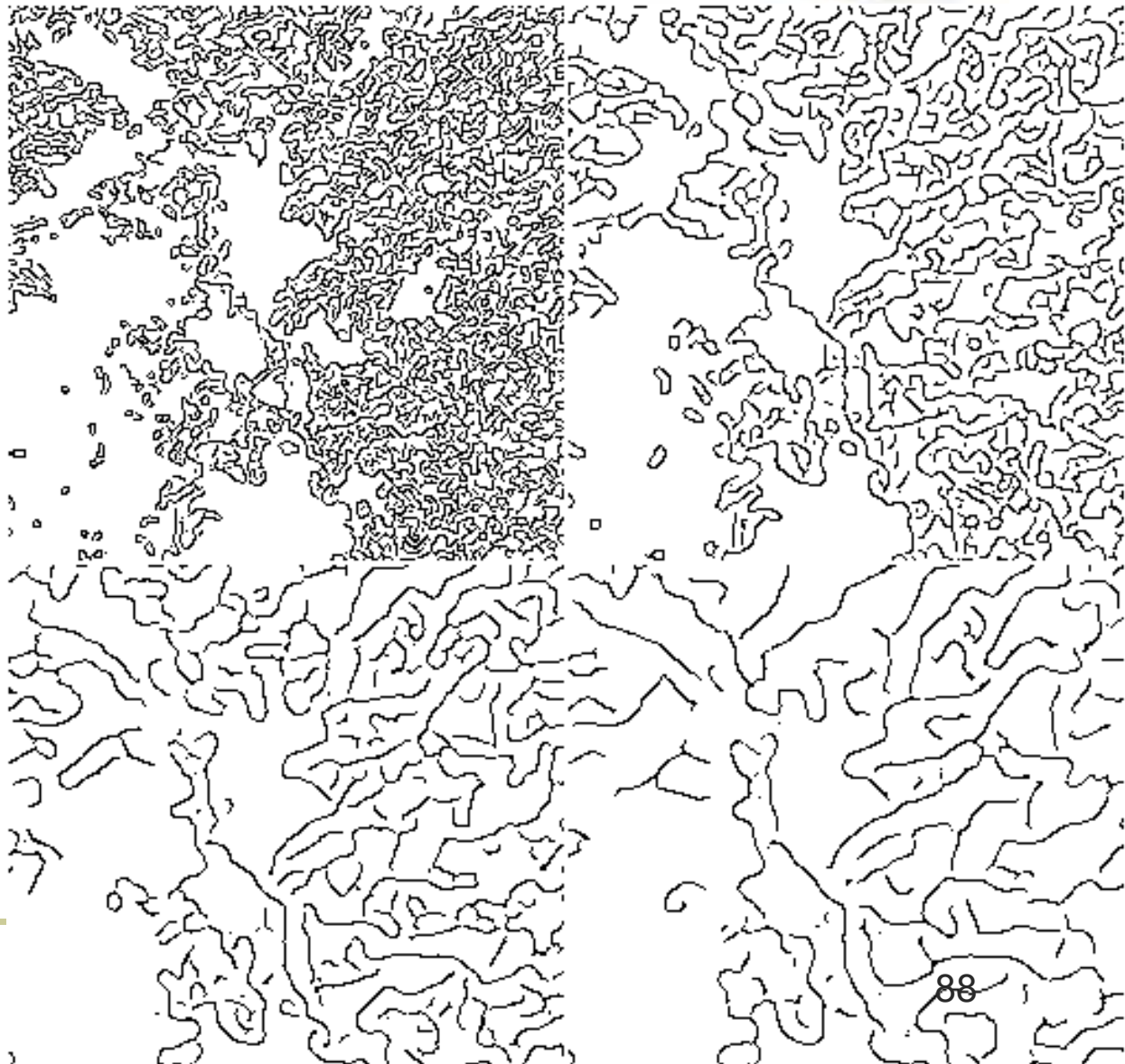
- large σ detects large scale edges
- small σ detects fine features

Example: Canny Edge Detection





Example: Canny Edge Detection



Low-level edges vs. perceived contours

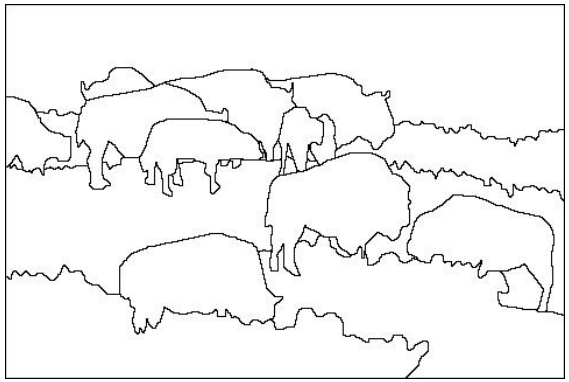
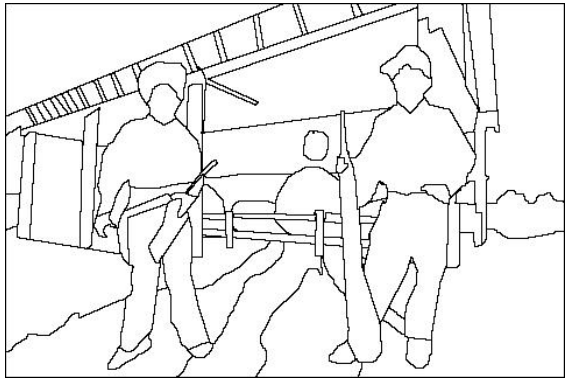
Background

Texture

Shadows




Low-level edges vs. perceived contours

image	human segmentation	gradient magnitude
		
		

- Berkeley segmentation database:
  http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics

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This paper presents a database containing 'ground truth' segmentations produced by humans for images of a wide variety of natural scenes. We define an error measure which quantifies the consistency between segmentations of differing granularities and find that different human segmentations of the same image are highly consistent. Use of this dataset is demonstrated in two applications: (1) evaluating the performance of segmentation algorithms and (2) measuring probability distributions associated with Gestalt grouping factors as well as statistics of image region properties.

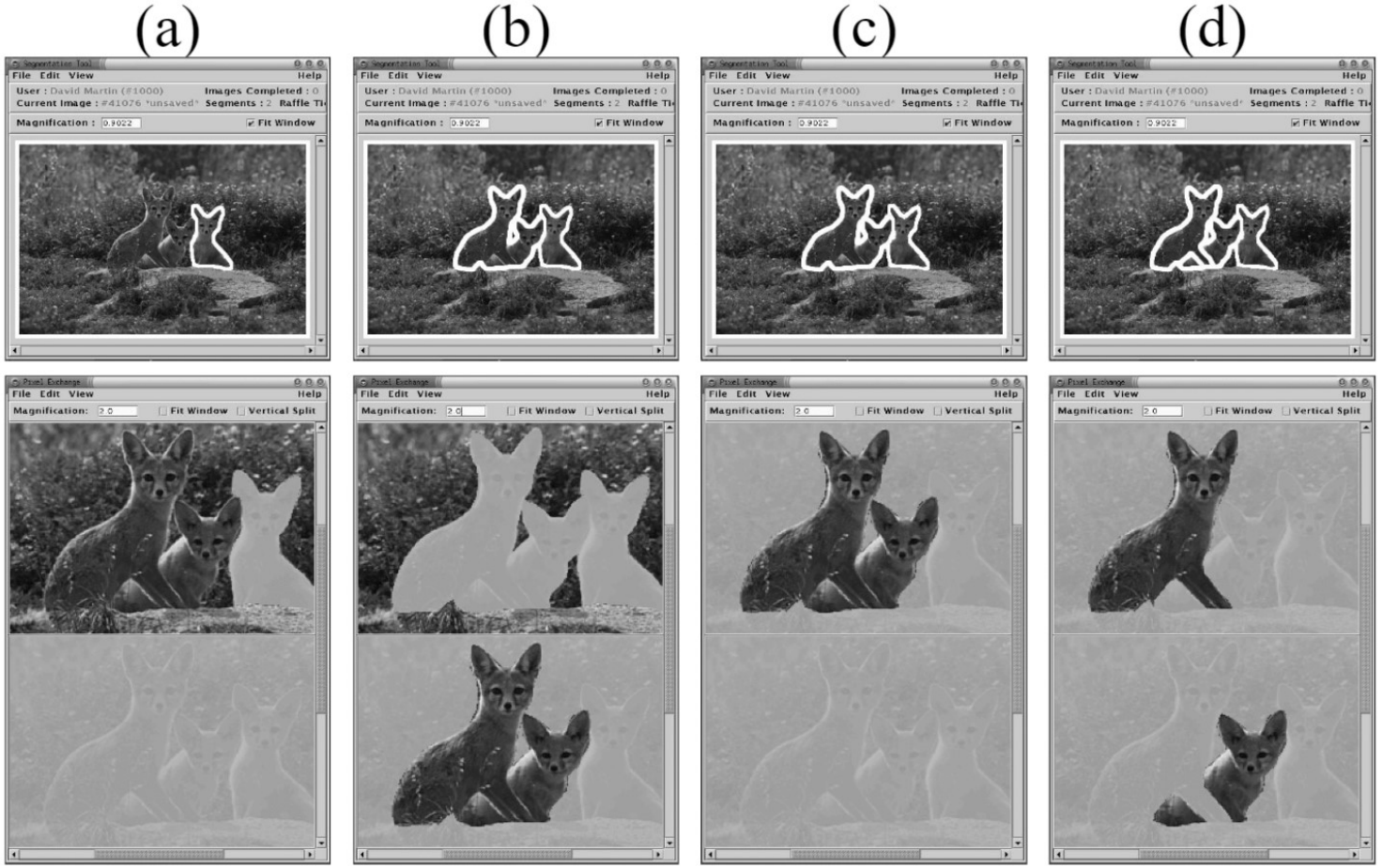
A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics
D Martin, C Fowlkes, D Tal… - Proceedings Eighth IEEE …, 2001 - ieeexplore.ieee.org
被引用次数：6400 相关文章 所有 18 个版本

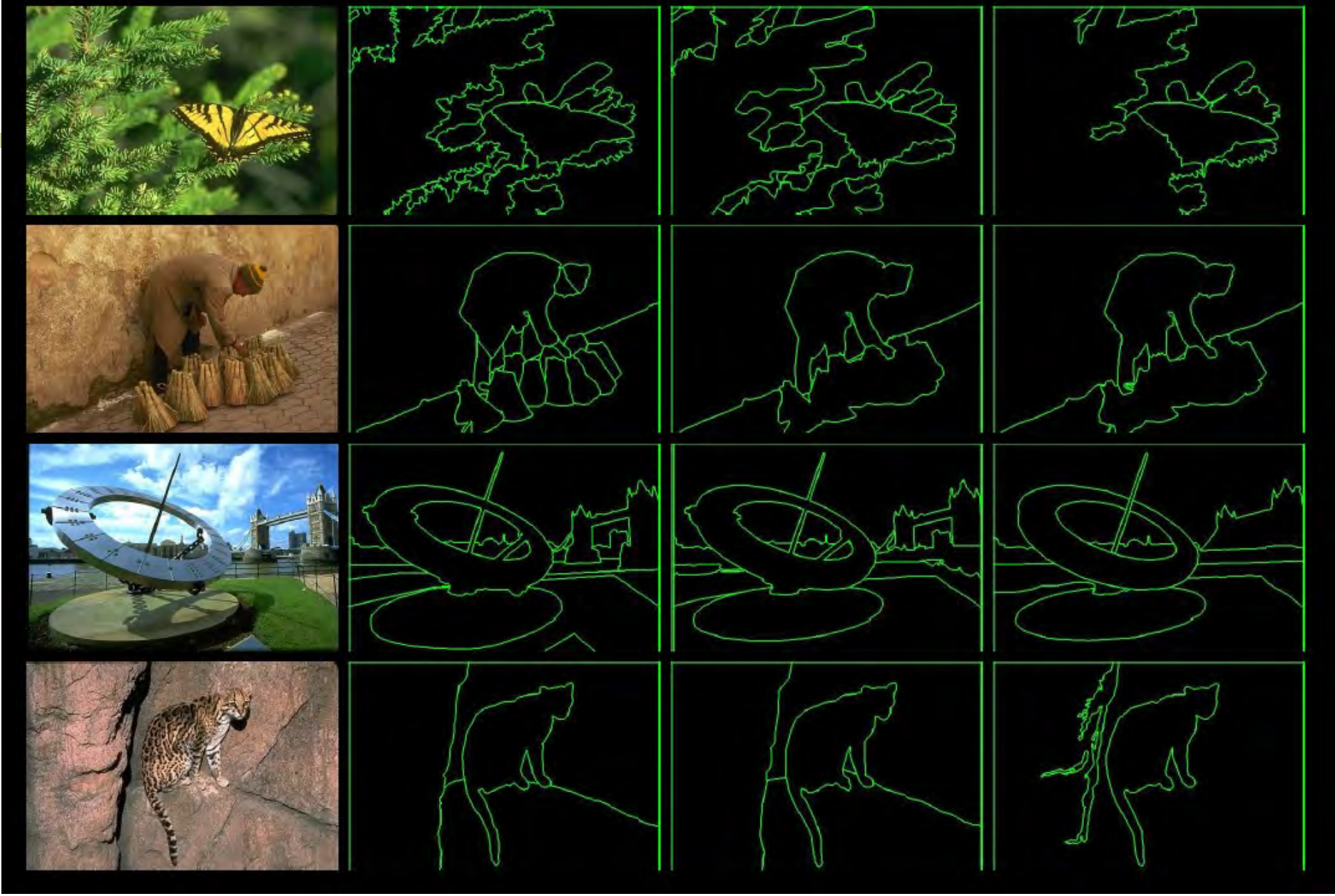
Protocol

You will be presented a photographic image. Divide the image into some number of segments, where the segments represent "things" or "parts of things" in the scene. The number of segments is up to you, as it depends on the image. Something between 2 and 30 is likely to be appropriate. It is important that all of the segments have approximately equal importance.

- Custom segmentation tool
- Subjects obtained from work-study program (UC Berkeley undergraduates)

Annotation tool





Segmentation Error Measure

- A segmentation is a division of the pixels an image into sets.
- A segmentation error takes two segmentations as input and produces a real-valued output.
- We define a measure error at each pixel that is **tolerant to refinement.**

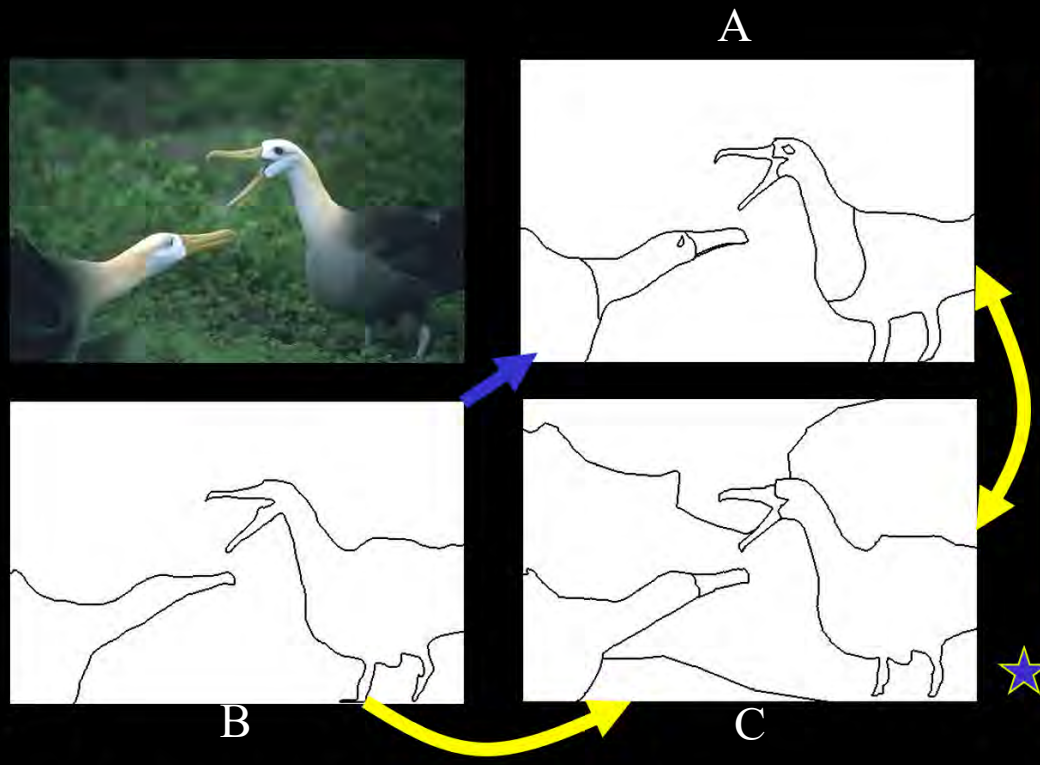
$$E(S_1, S_2, p_i) = \frac{|R(S_1, p_i) \backslash R(S_2, p_i)|}{|R(S_1, p_i)|}$$

GCE vs. LCE

$$GCE(S_1, S_2) = \frac{1}{n} \min \left\{ \sum_i E(S_1, S_2, p_i), \sum_i E(S_2, S_1, p_i) \right\} \quad (2)$$

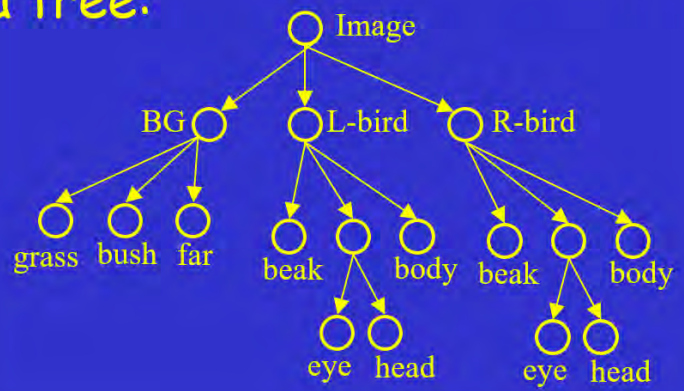
$$LCE(S_1, S_2) = \frac{1}{n} \sum_i \min \left\{ E(S_1, S_2, p_i), E(S_2, S_1, p_i) \right\} \quad (3)$$

Consistency



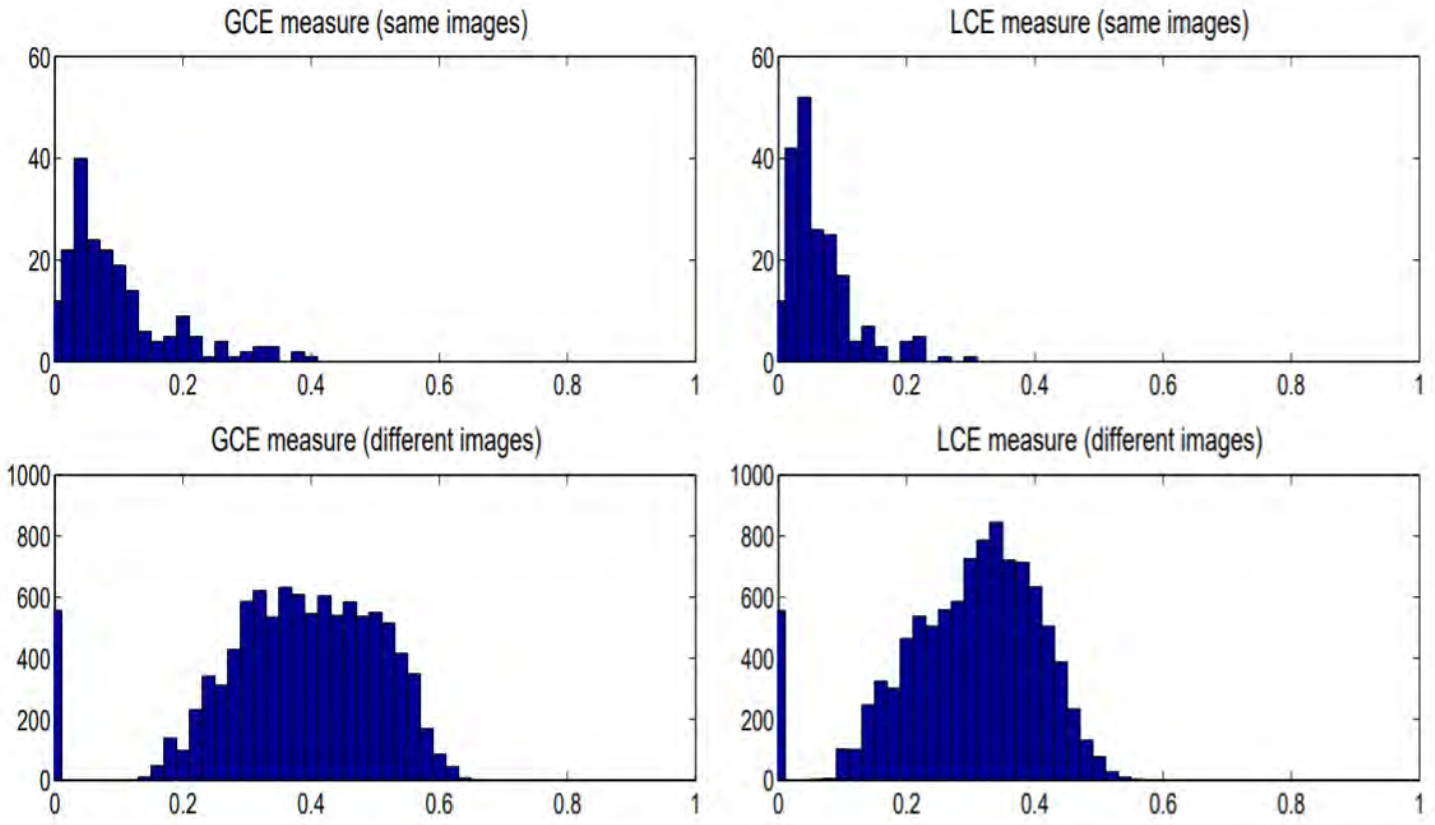
- A,C are refinements of B
- A,C are mutual refinements
- A,B,C represent the same percept
  - Attention accounts for differences

Perceptual organization forms a tree:

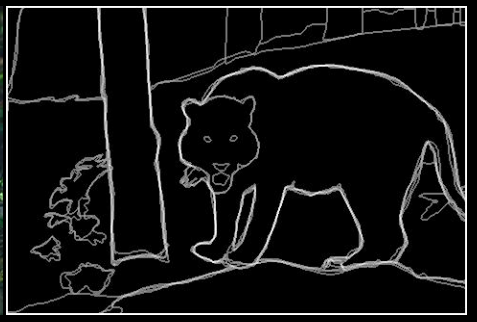


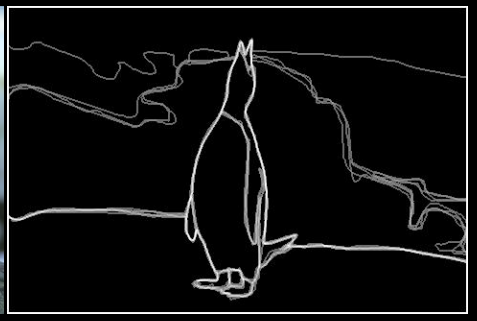
☆ Two segmentations are consistent when they can be explained by the same segmentation tree (i.e. they could be derived from a single perceptual organization).

Error Measure Validation





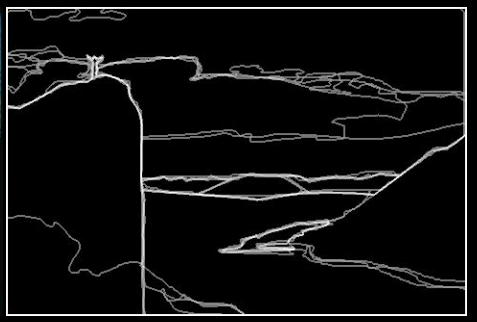












Dataset Summary

- 30 subjects, age 19-23
  - 17 men, 13 women
  - 9 with artistic training
- 8 months
- 1,458 person hours
- 1,020 Corel images
- 11,595 Segmentations
  - 5,555 color, 5,554 gray, 486 inverted/negated

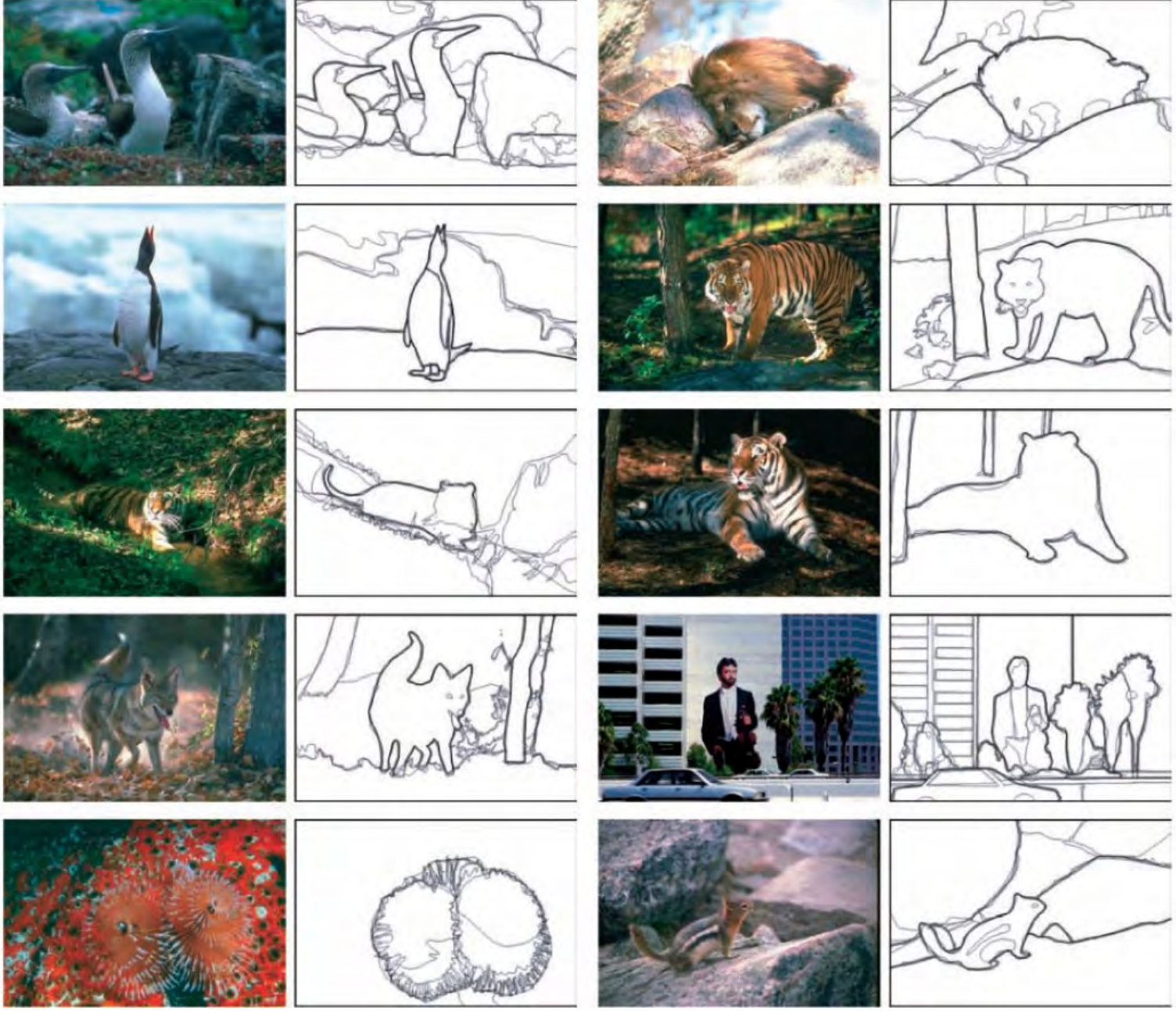
Learning to Detect Natural Image Boundaries Using Local Brightness, Color, and Texture Cues

David R. Martin, *Member*, *IEEE*, Charless C. Fowlkes, and Jitendra Malik, *Member*, *IEEE*

Abstract—The goal of this work is to accurately detect and localize boundaries in natural scenes using local image measurements. We formulate features that respond to characteristic changes in brightness, color, and texture associated with natural boundaries. In order to combine the information from these features in an optimal way, we train a classifier using human labeled images as ground truth. The output of this classifier provides the posterior probability of a boundary at each image location and orientation. We present precision-recall curves showing that the resulting detector significantly outperforms existing approaches. Our two main results are 1) that cue combination can be performed adequately with a simple linear model and 2) that a proper, explicit treatment of texture is required to detect boundaries in natural images.

Index Terms—Texture, supervised learning, cue combination, natural images, ground truth segmentation data set, boundary detection, boundary localization.

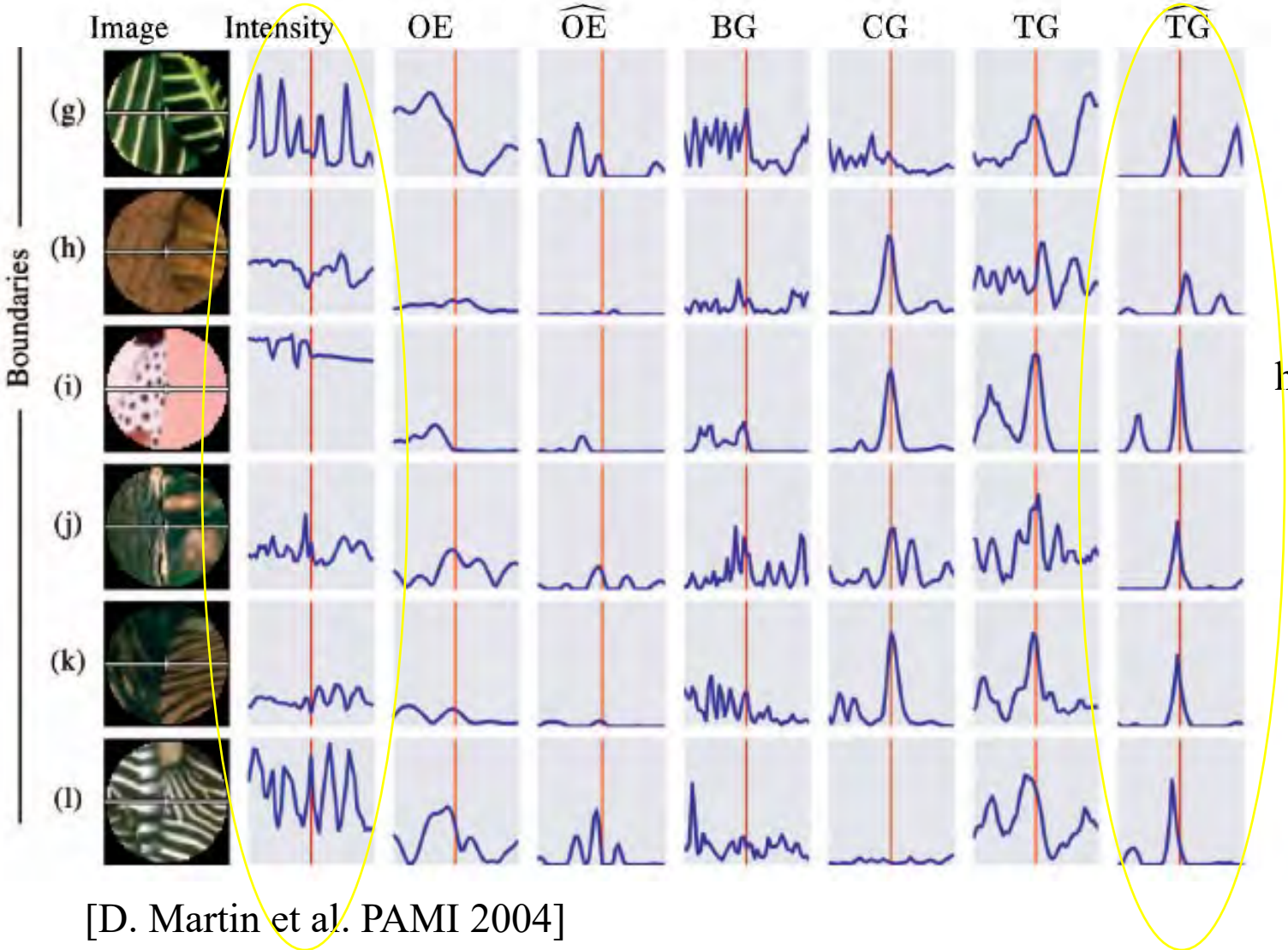
Learn from humans which combination of features is most indicative of a "good" contour?



[D. Martin et al. PAMI 2004]

Human-marked segment boundaries

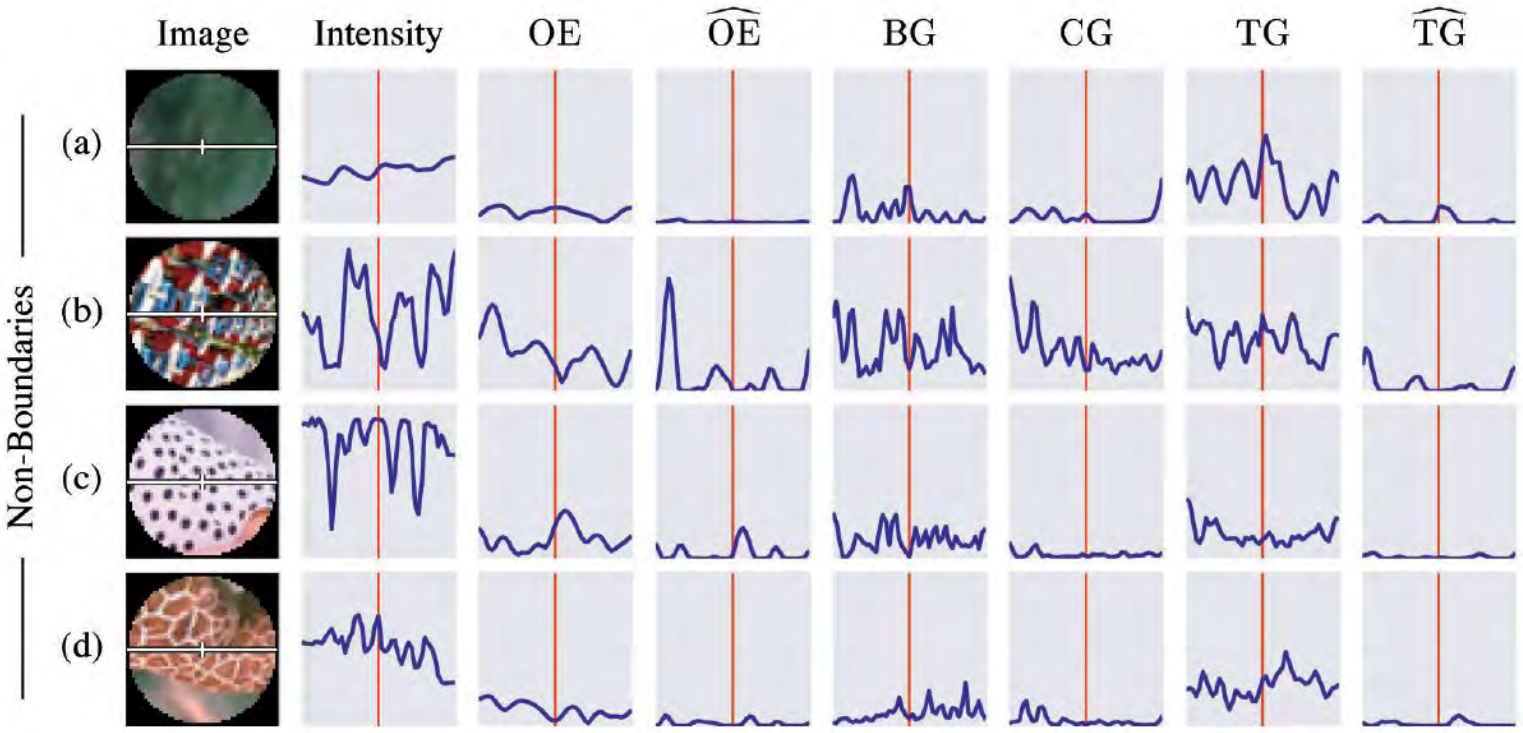
What features are responsible for perceived edges?



Feature profiles (oriented energy, brightness, color, and texture gradients) along the patch's horizontal diameter

[D. Martin et al. PAMI 2004]

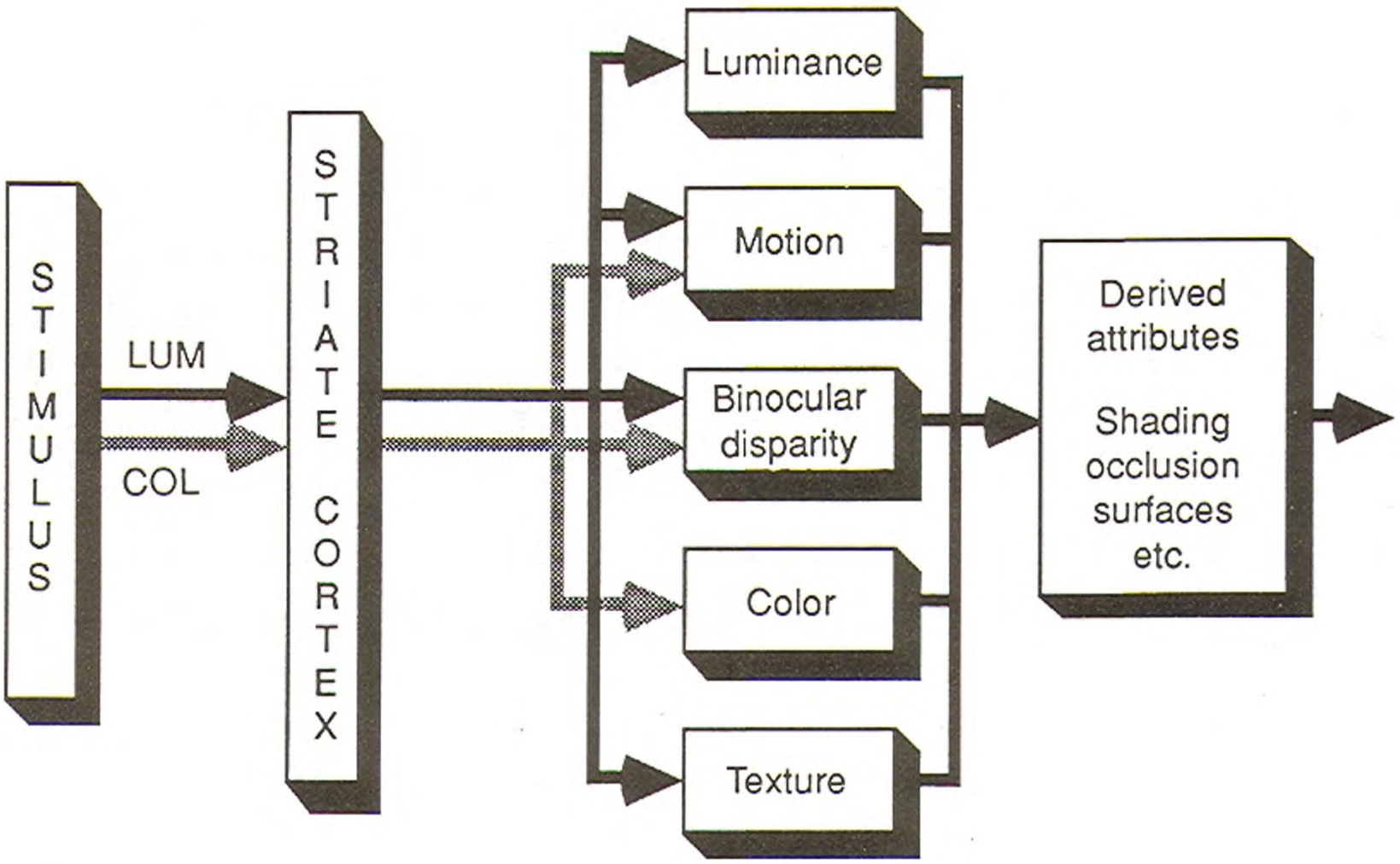
What features are responsible for perceived edges?



Feature profiles (oriented energy, brightness, color, and texture gradients) along the patch's horizontal diameter

[D. Martin et al. PAMI 2004]

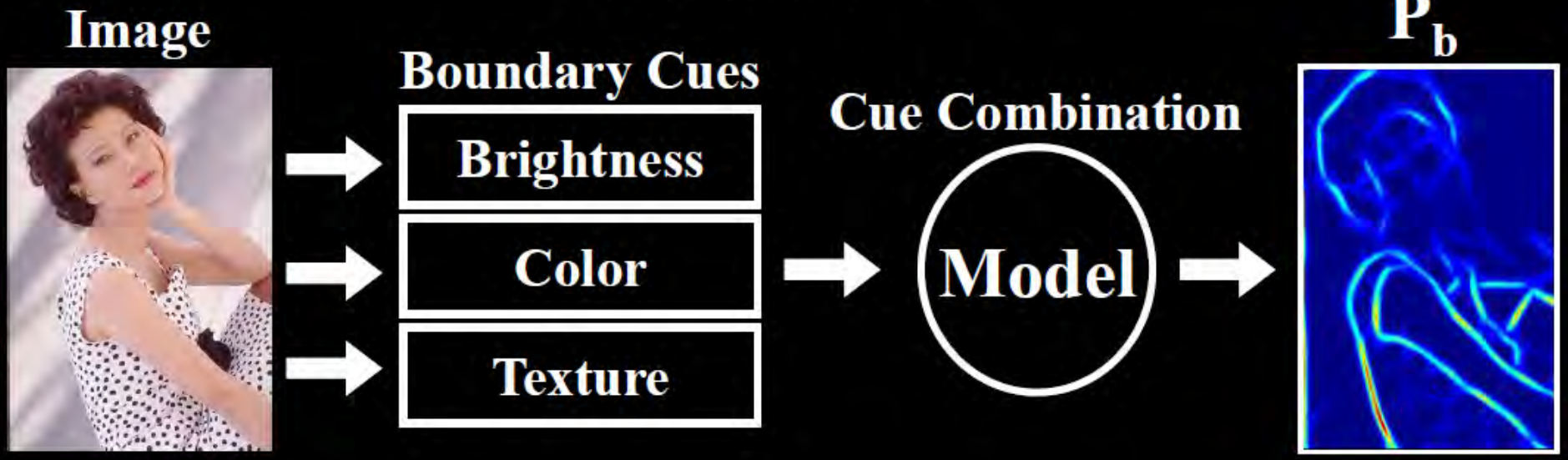
Contours can be defined by any of a number of cues (P. Cavanagh)



Boundaries of image regions defined by a number of cues

- Brightness
- Color
- Texture
- Motion (in video)
- Binocular Diparity (if available)
- Familiar objects

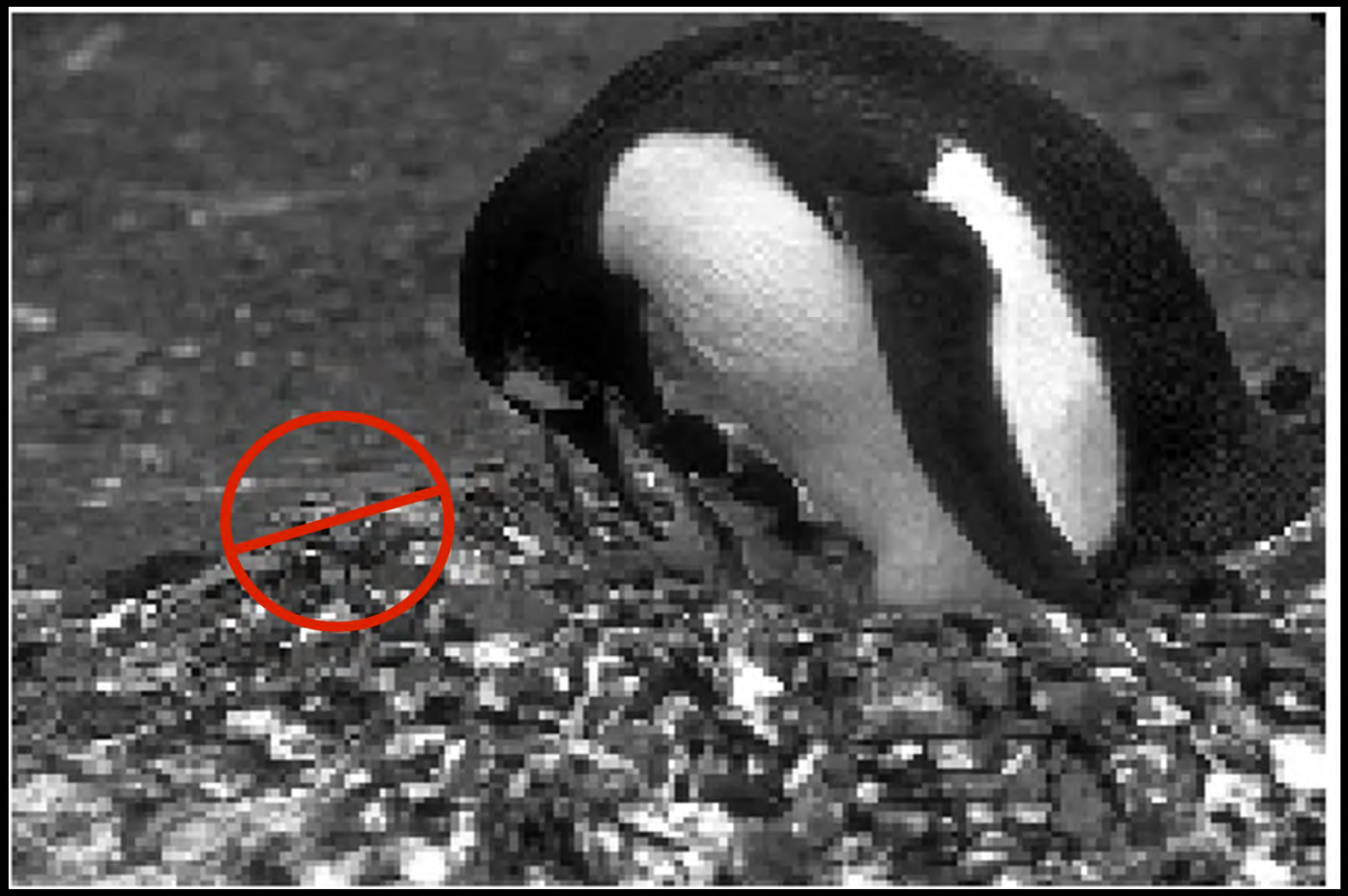
Dataflow



Challenges: texture cue, cue combination

Goal: learn the posterior probability of a boundary $P_b(x,y,\theta)$ from local information only

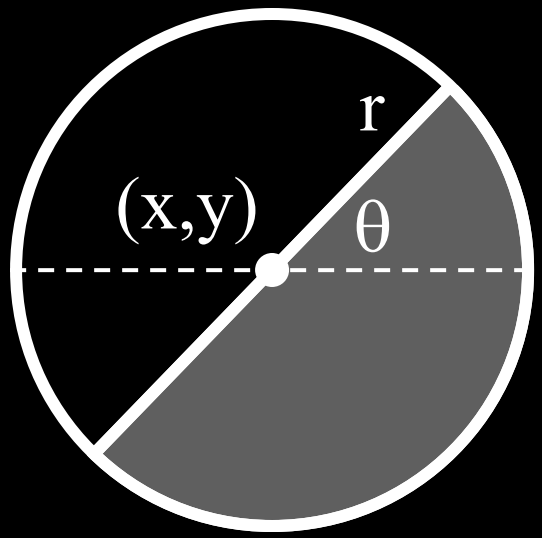
Oriented Feature Gradient



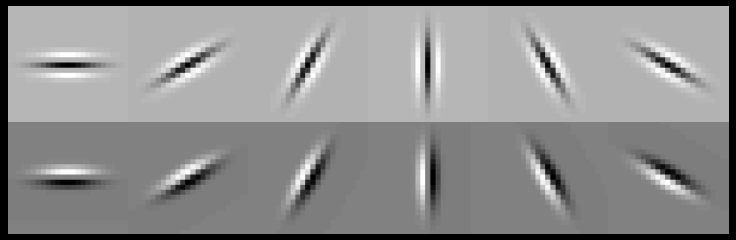
Brightness and Color Features

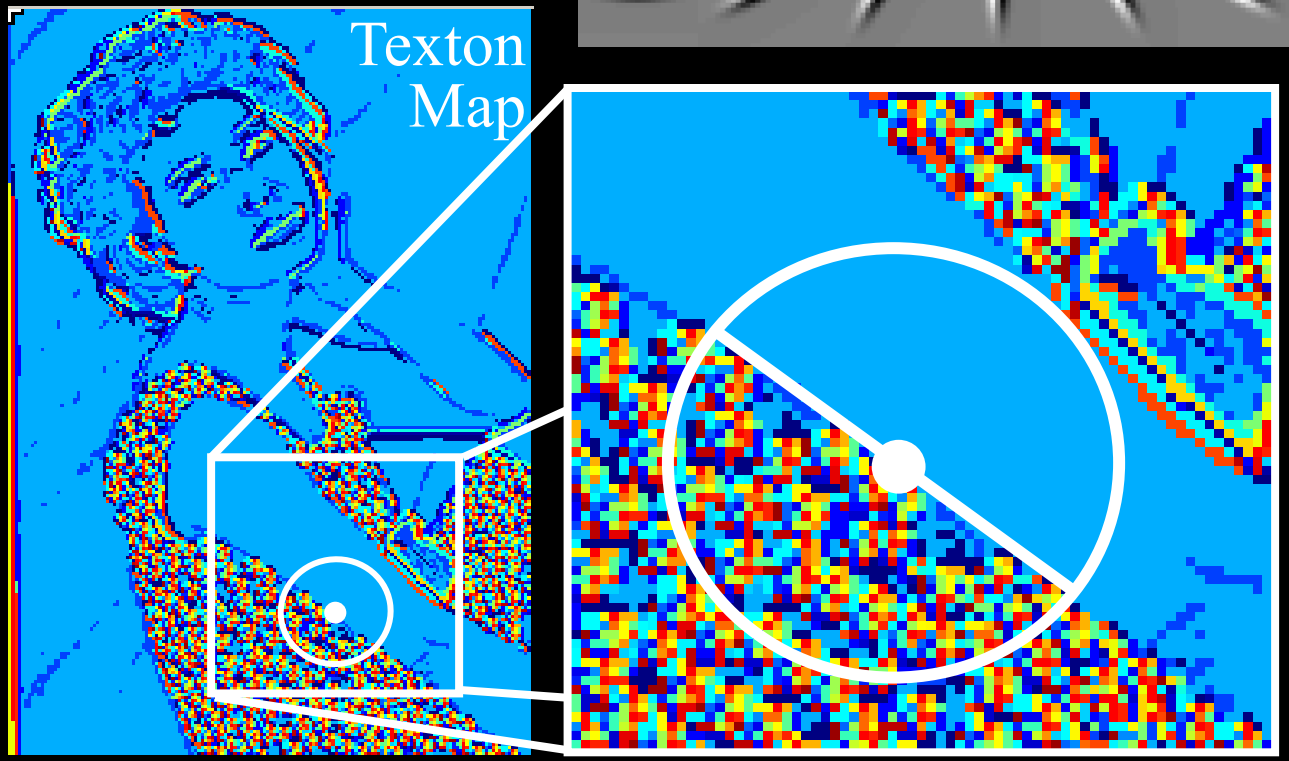
- 1976 CIE L*a*b* colorspace
- Brightness Gradient BG(x,y,r,θ)
  - χ^2 difference in L* distribution
- Color Gradient CG(x,y,r,θ)
  - χ^2 difference in a* and b* distributions

$$\chi^2(g,h) = \frac{1}{2}\sum_i \frac{(g_i - h_i)^2}{g_i + h_i}$$



Texture Feature

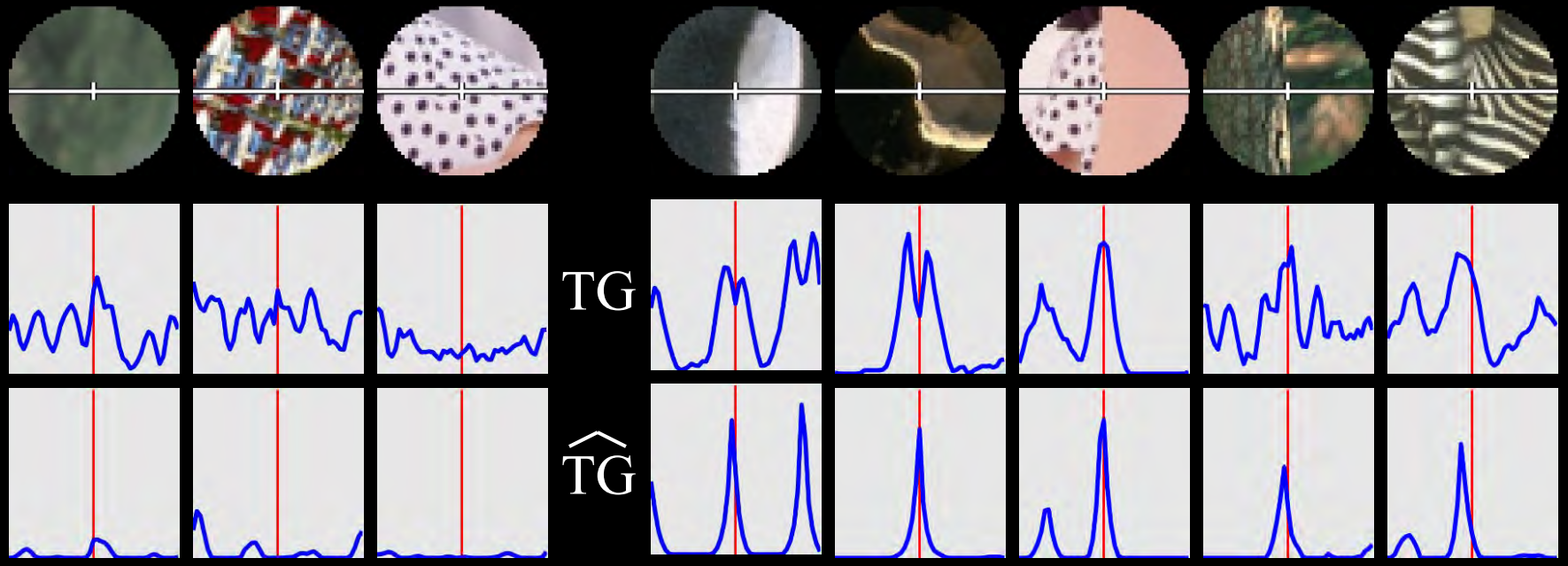




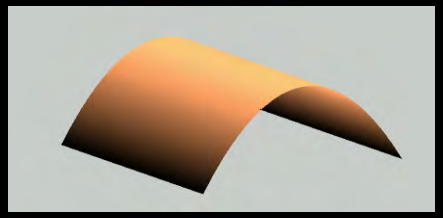
- Texture Gradient TG(x,y,r,θ)
  - χ^2 difference of texton histograms
  - Textons are vector-quantized filter outputs

Boundary Localization

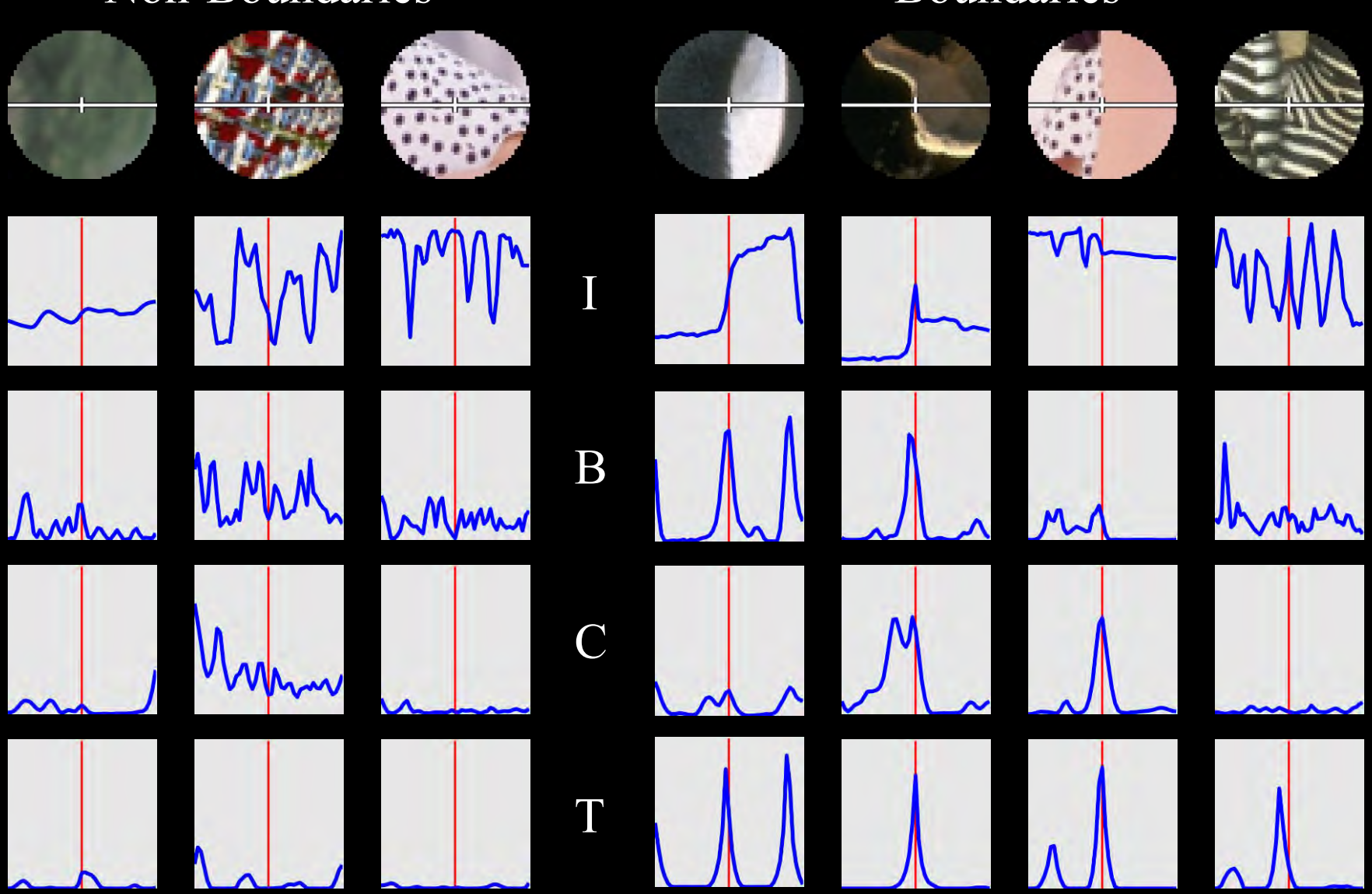
Non-Boundaries — Boundaries



(1) Fit cylindrical parabolas to raw oriented signal to get local shape: (Savitsky-Golay)



(2) Localize peaks: $\hat{f} = \tilde{f} \cdot \left(\frac{-f''}{|f'| + \varepsilon} \right)$


Non-Boundaries
Boundaries
I
B
C
T

Cue Combination Models

- Classification Trees
  - Top-down splits to maximize entropy, error bounded
- Density Estimation
  - Adaptive bins using k-means
- Logistic Regression, 3 variants
  - Linear and quadratic terms
  - Confidence-rated generalization of AdaBoost (Schapire&Singer)
- Hierarchical Mixtures of Experts (Jordan&Jacobs)
  - Up to 8 experts, initialized top-down, fit with EM
- Support Vector Machines (`libsvm`, Chang&Lin)
  - Gaussian kernel, ν-parameterization

➢ Range over bias, complexity, parametric/non-parametric

Computing Precision/Recall

Recall = Pr(signal|truth) = fraction of ground truth found by the signal

Precision = Pr(truth|signal) = fraction of signal that is correct

- Always a trade-off between the two
- Standard measures in information retrieval (van Rijsbergen XX)
- ROC from standard signal detection the wrong approach

Strategy

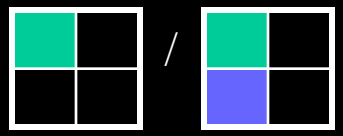
- Detector output (Pb) is a soft boundary map
- Compute precision/recall curve:
  - Threshold Pb at many points t in [0,1]
  - Recall = Pr(Pb>t|seg=1)
  - Precision = Pr(seg=1|Pb>t)

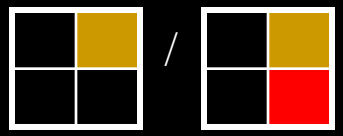
ROC vs. Precision/Recall

$$F = \max_t \left\{ \frac{2pr}{p+r} \right\}$$

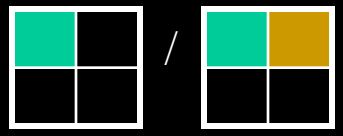
Signal \ Truth	P	N
P	TP	FP
N	FN	TN

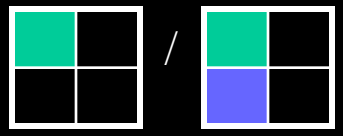
ROC Curve

Hit Rate = TP / (TP+FN) = 

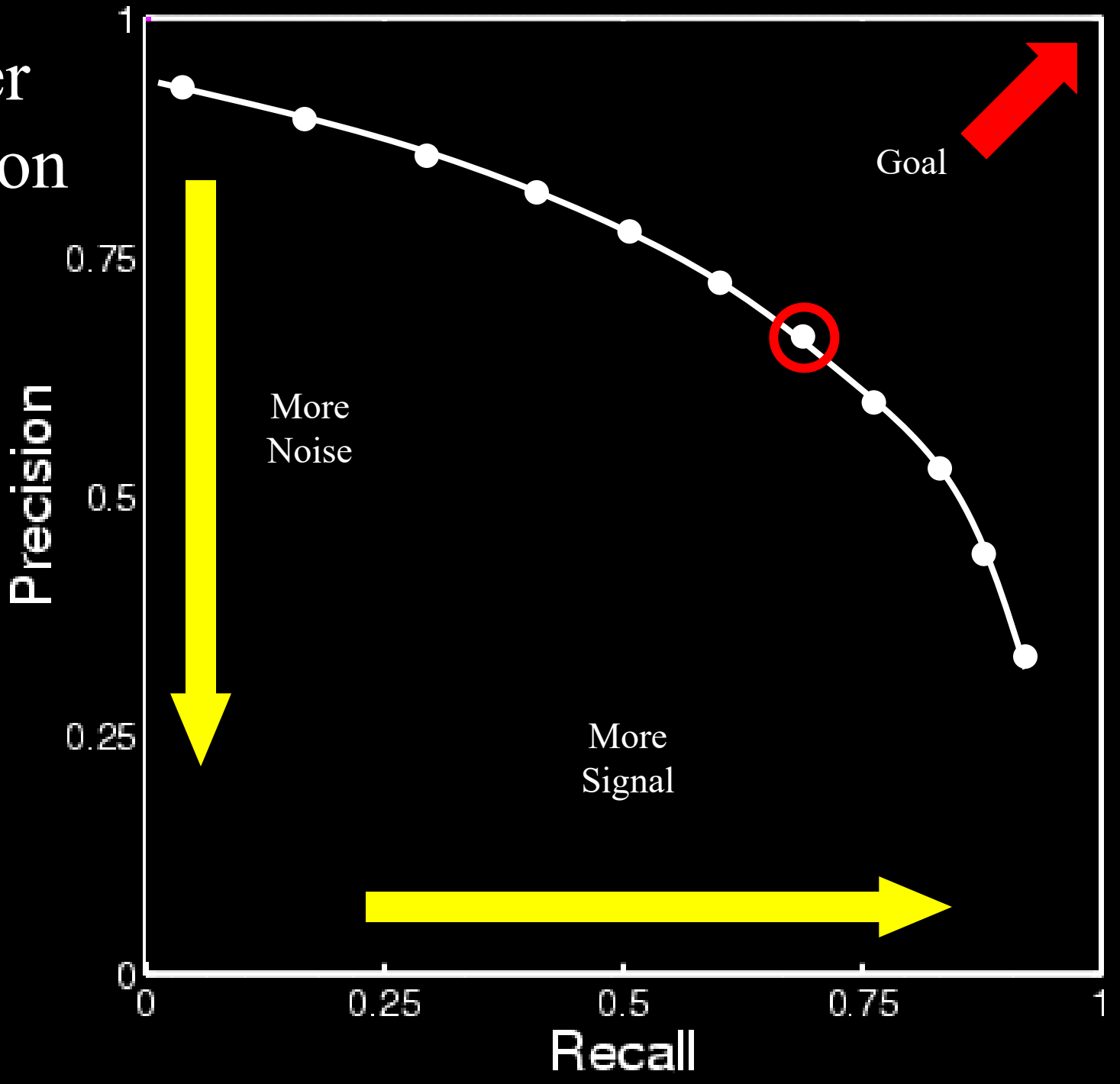
False Alarm Rate = FP / (FP+TN) = 

PR Curve

Precision = TP / (TP+FP) = 

Recall = TP / (TP+FN) = 

Classifier Comparison



Cue Calibration

- All free parameters optimized on training data
- All algorithmic alternatives evaluated by experiment

- Brightness Gradient
  - Scale, bin/kernel sizes for KDE
- Color Gradient
  - Scale, bin/kernel sizes for KDE, joint vs. marginals
- Texture Gradient
  - Filter bank: scale, multiscale?
  - Histogram comparison: L^1, L^2, L^∞, χ^2, EMD
  - Number of textons, Image-specific vs. universal textons
- Localization parameters for each cue

Dataflow

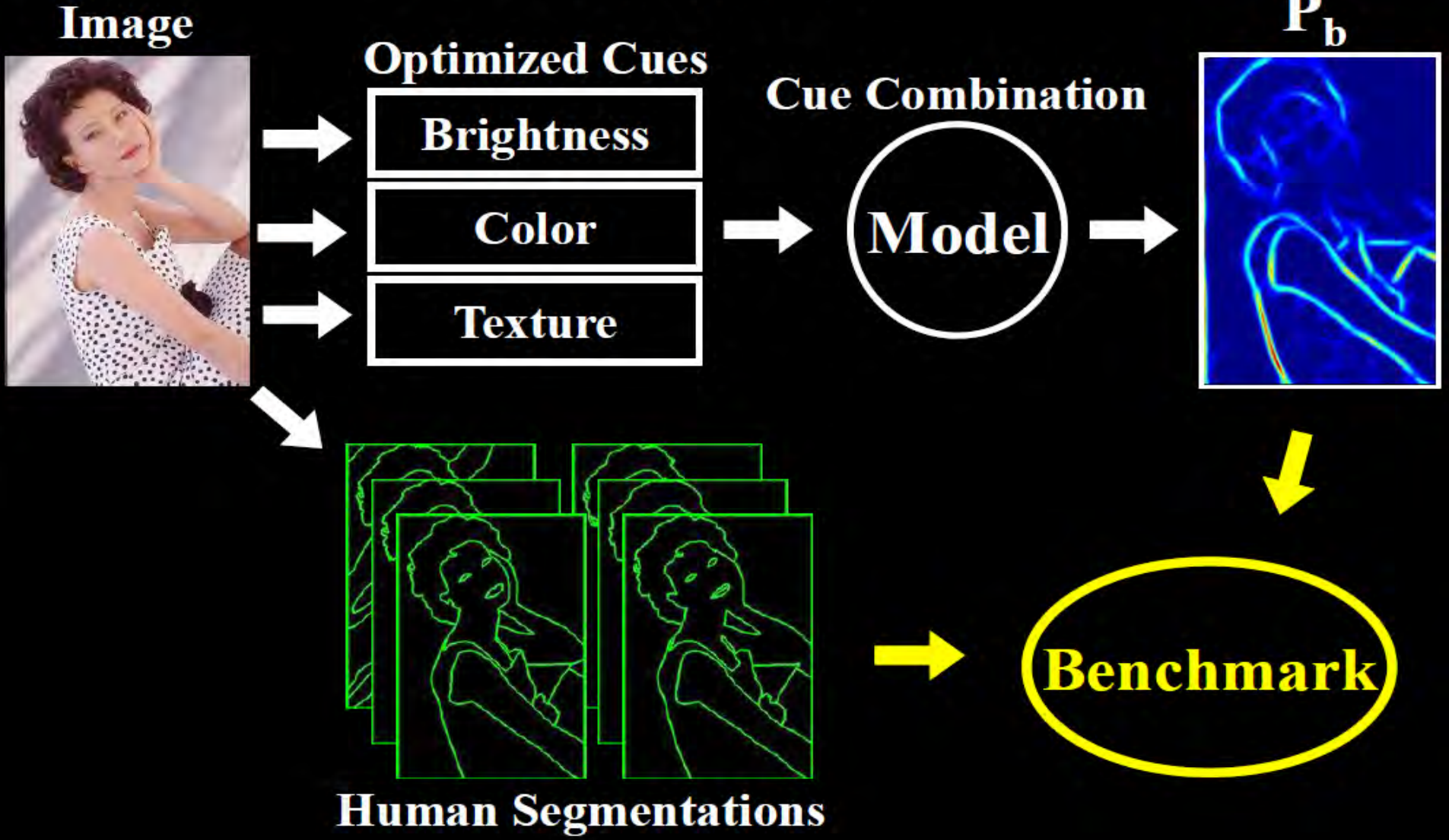
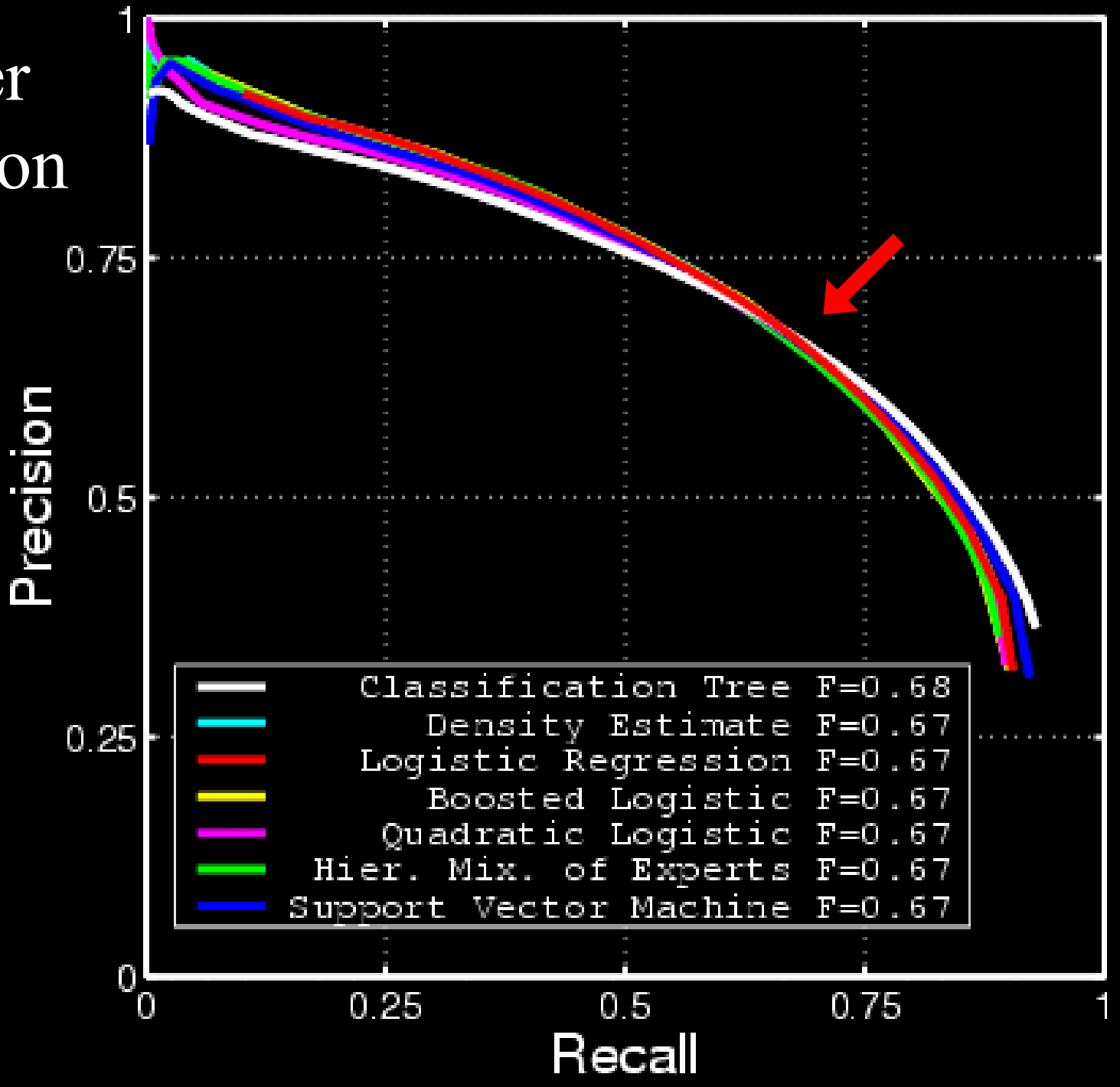


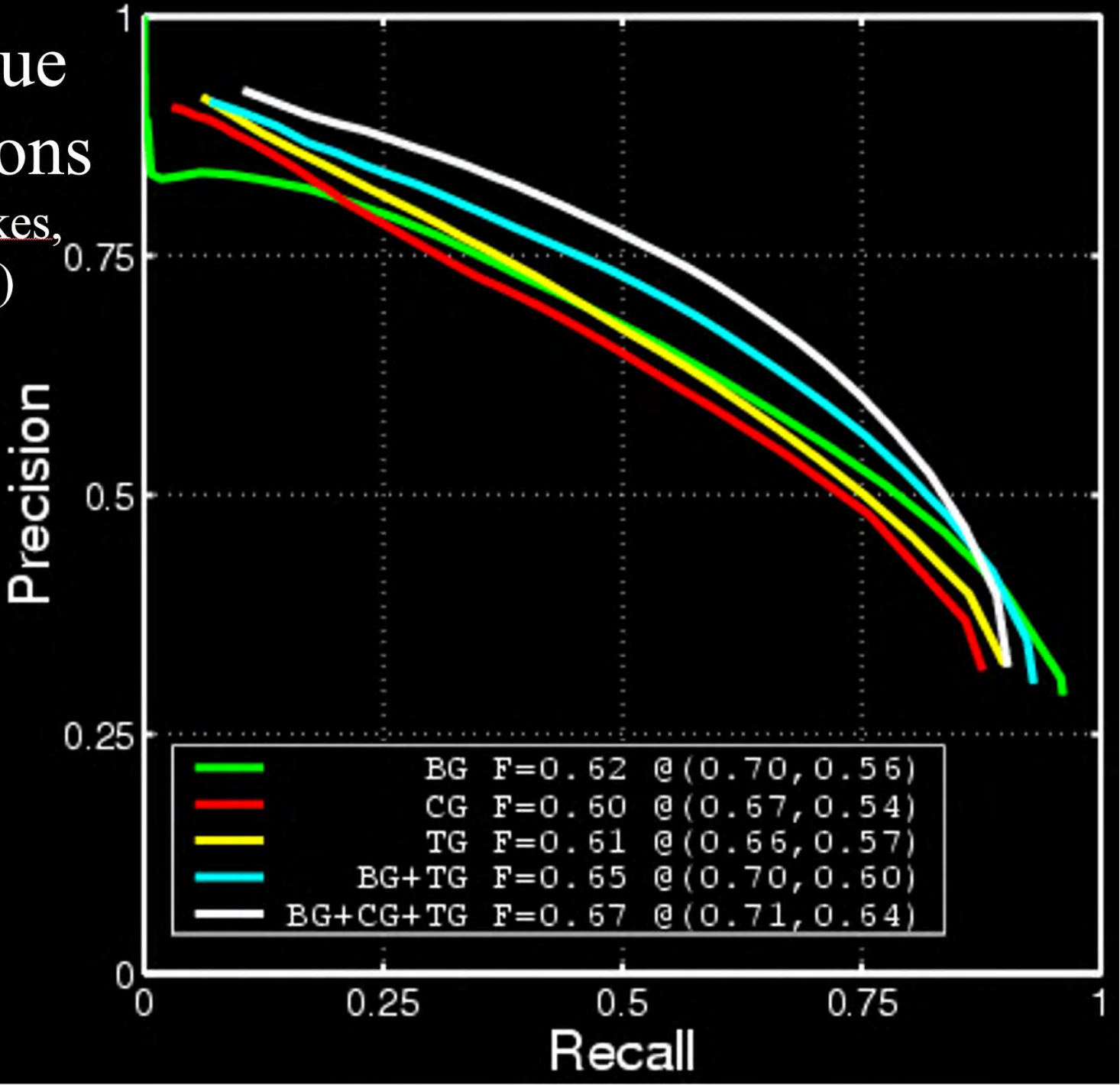
Image
Optimized Cues
Brightness
Color
Texture
Cue Combination
Model
P_b
Human Segmentations
Benchmark

Classifier Comparison



Various Cue Combinations

(Martin, Fowlkes, Malik, 2004)

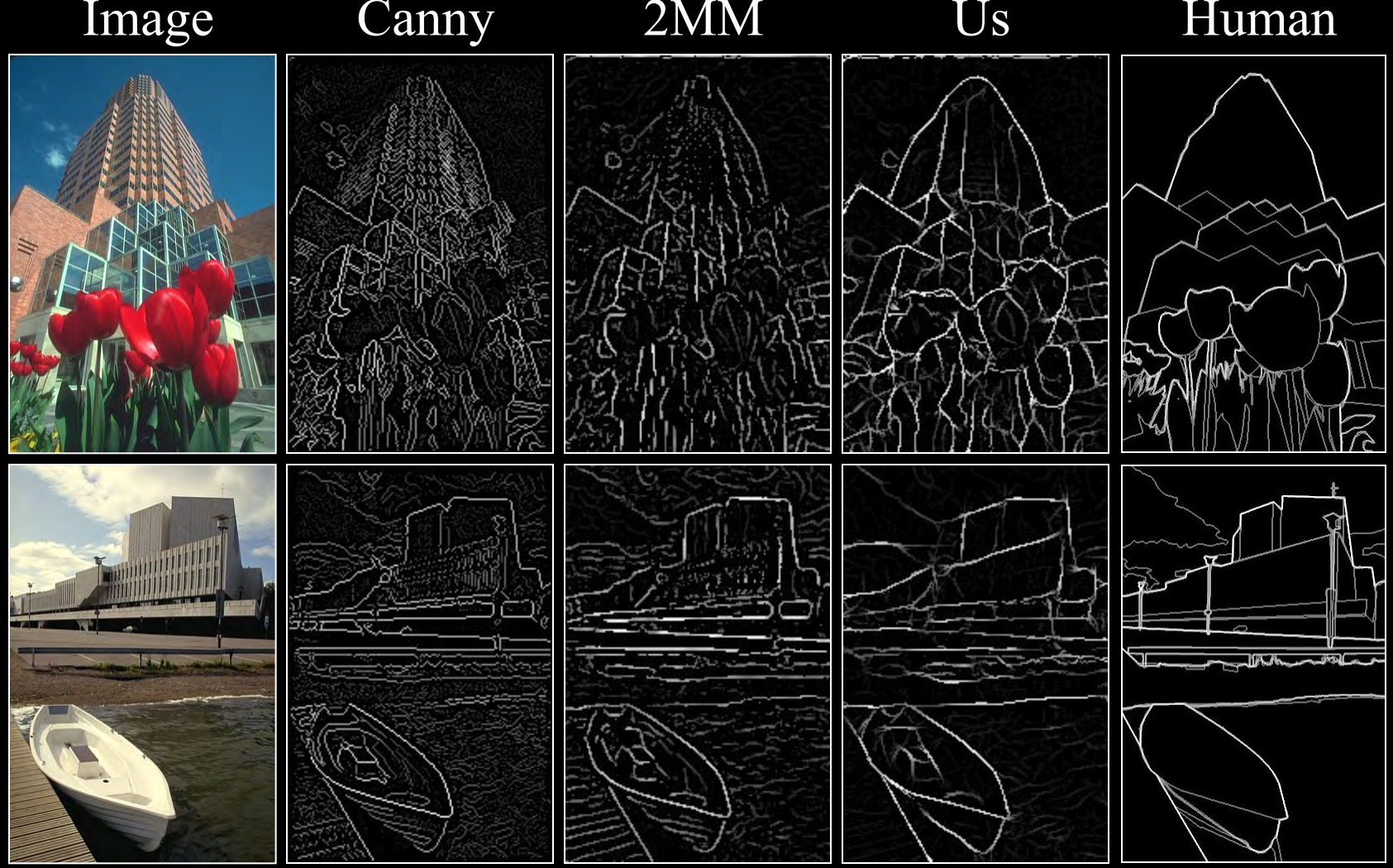


Alternate Approaches

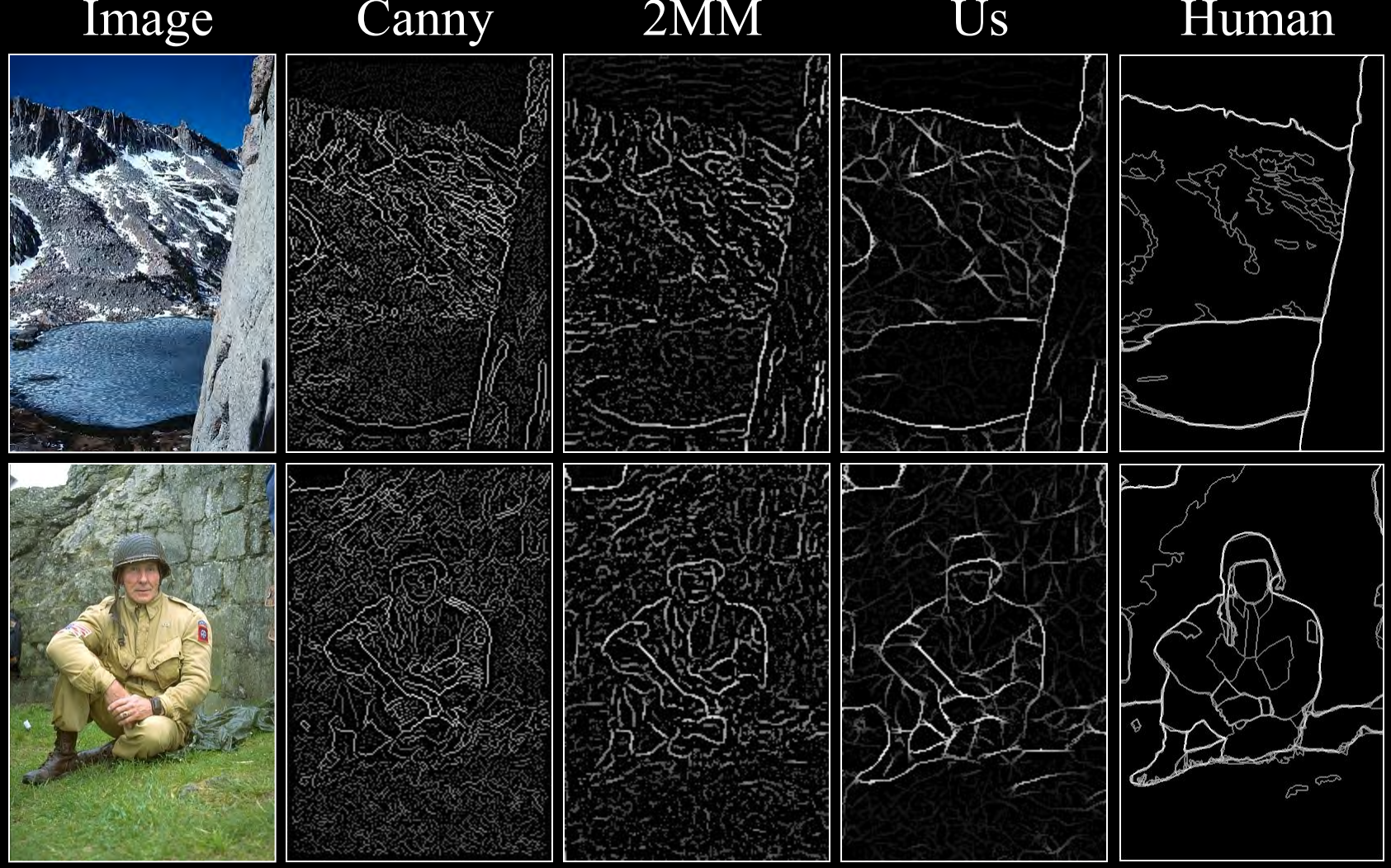
- Canny Detector
  - Canny 1986
  - MATLAB implementation
  - With and without hysteresis
- Second Moment Matrix
  - Nitzberg/Mumford/Shiota 1993
  - cf. Förstner and Harris corner detectors
  - Used by Konishi et al. 1999 in learning framework
  - Logistic model trained on full eigenspectrum

P_b Images

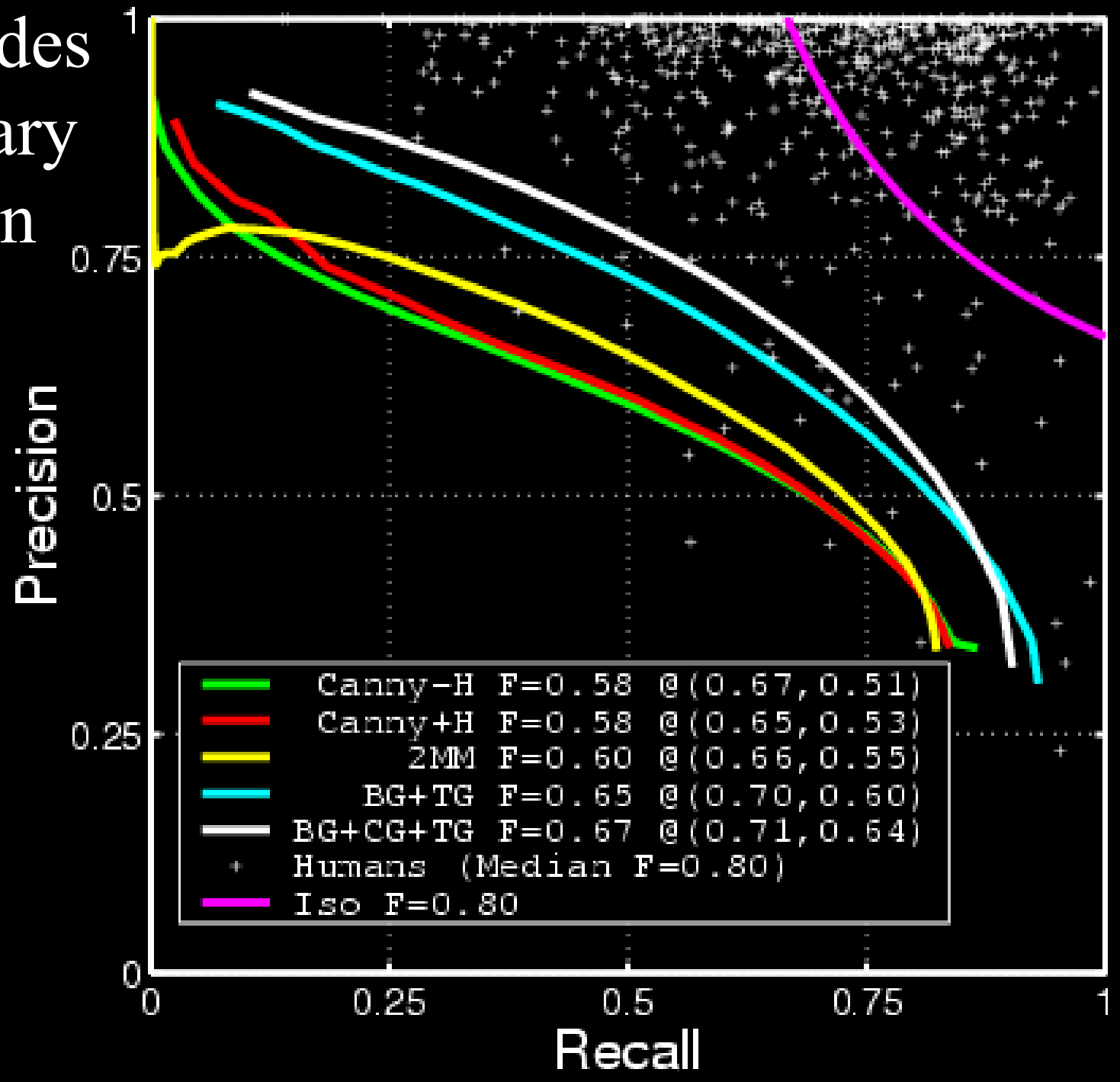
P_b Images II



P_b Images III



Two Decades of Boundary Detection



Findings

1. A simple linear model is sufficient for cue combination
   - All cues weighted approximately equally in logistic
2. Proper texture edge model is not optional for complex natural images
   - Texture suppression is not sufficient!
3. Significant improvement over state-of-the-art in boundary detection
   - $P_b(x,y,\theta)$ useful for higher-level processing
4. Empirical approach critical for both cue calibration and cue combination

[D. Martin et al. PAMI 2004]

Brightness

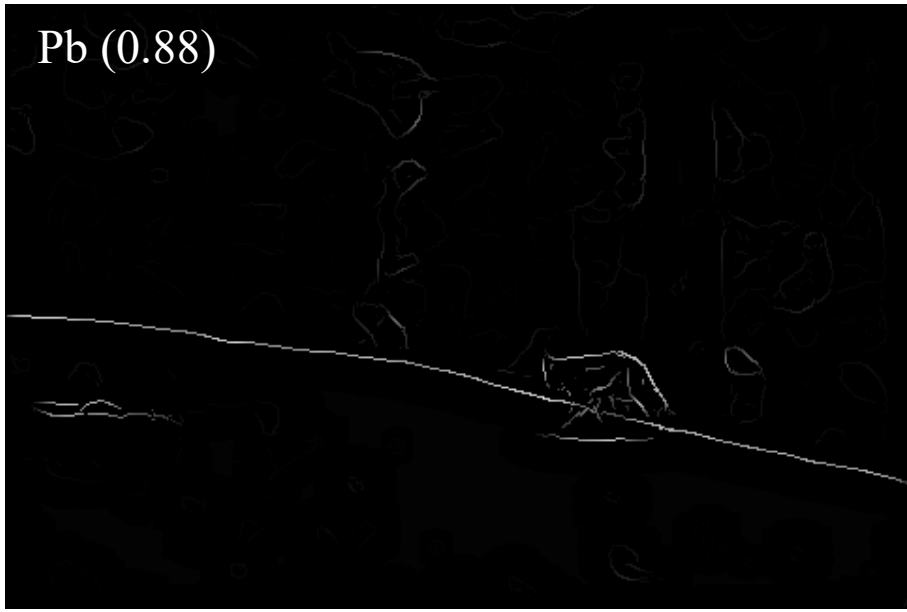
Color

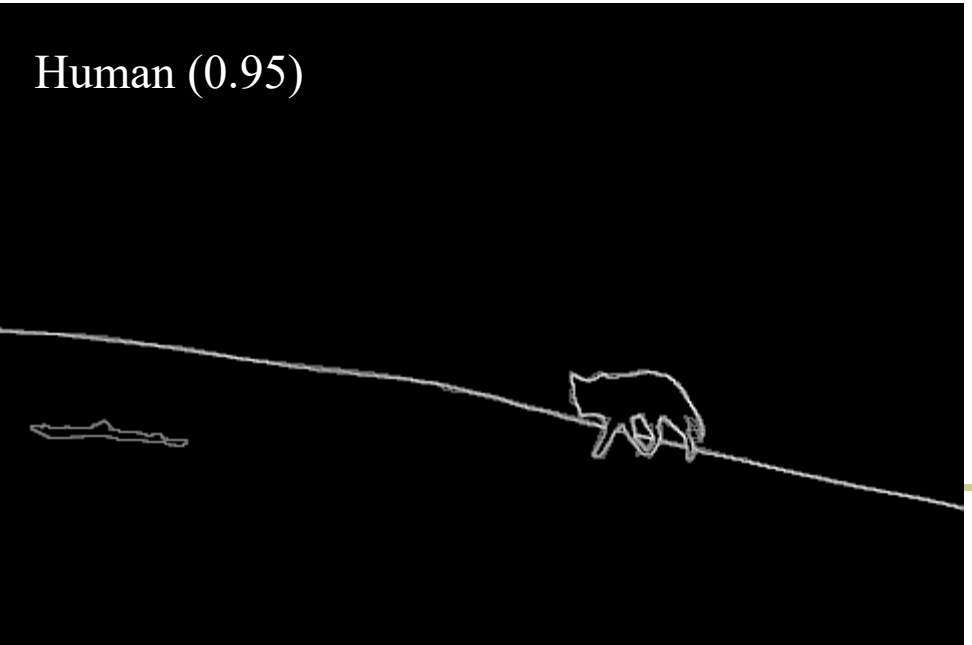
Texture

Combined

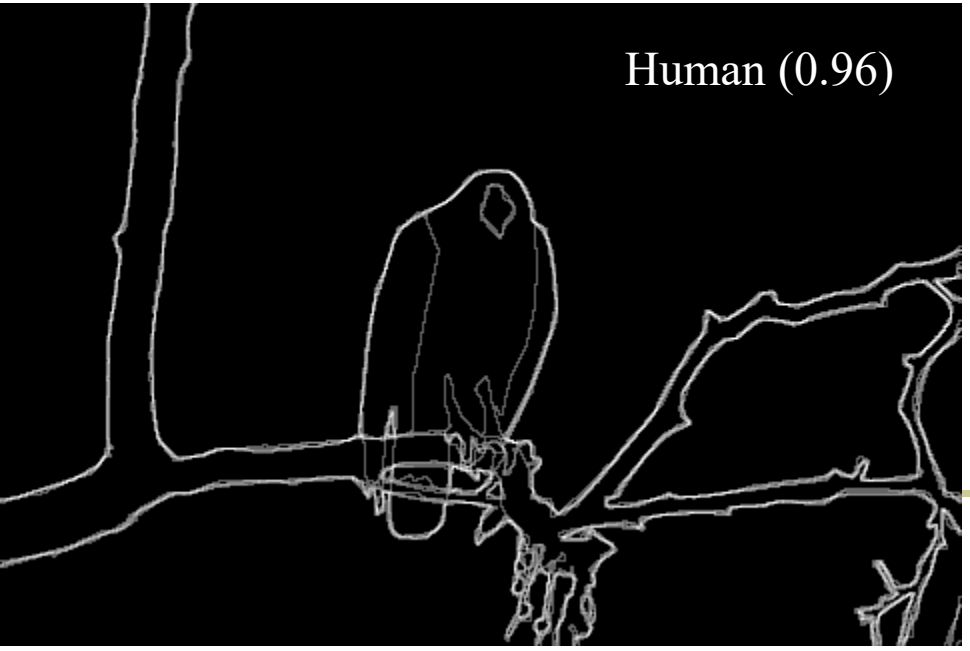
Human

Results

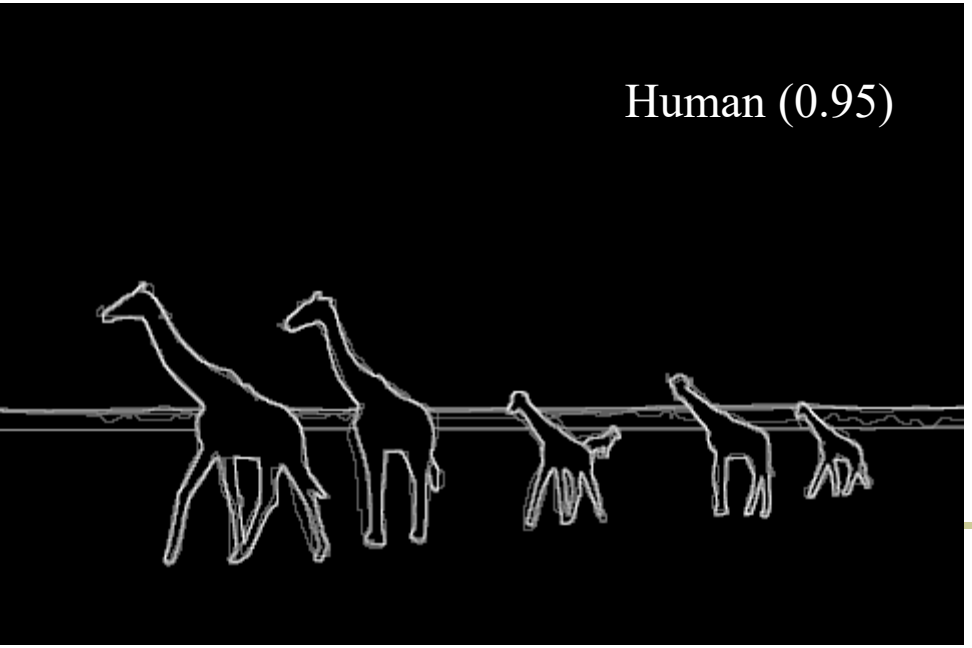


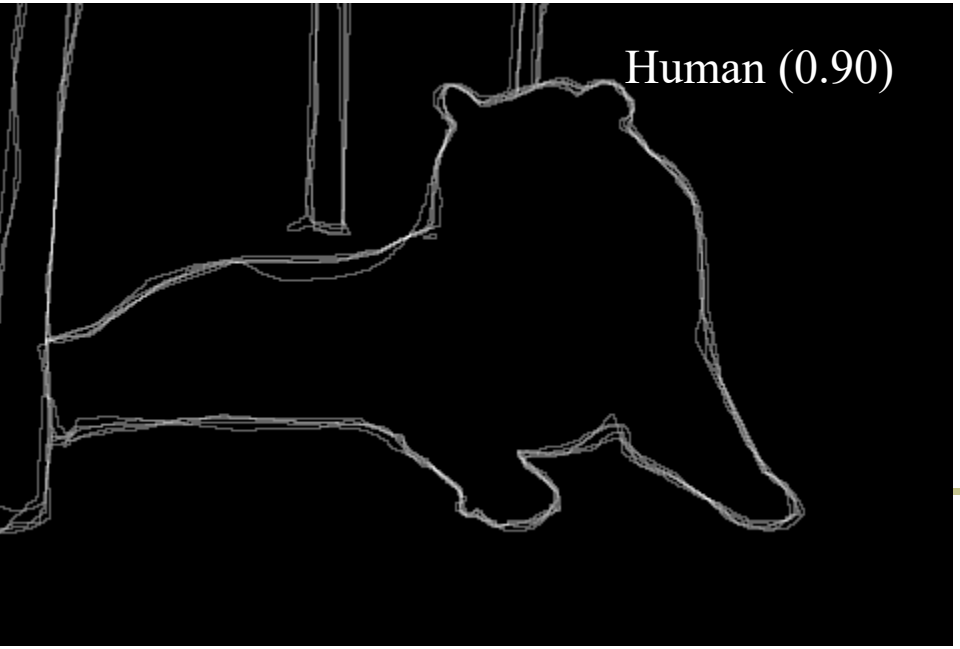


Results




Pb (0.63)


Human (0.95)



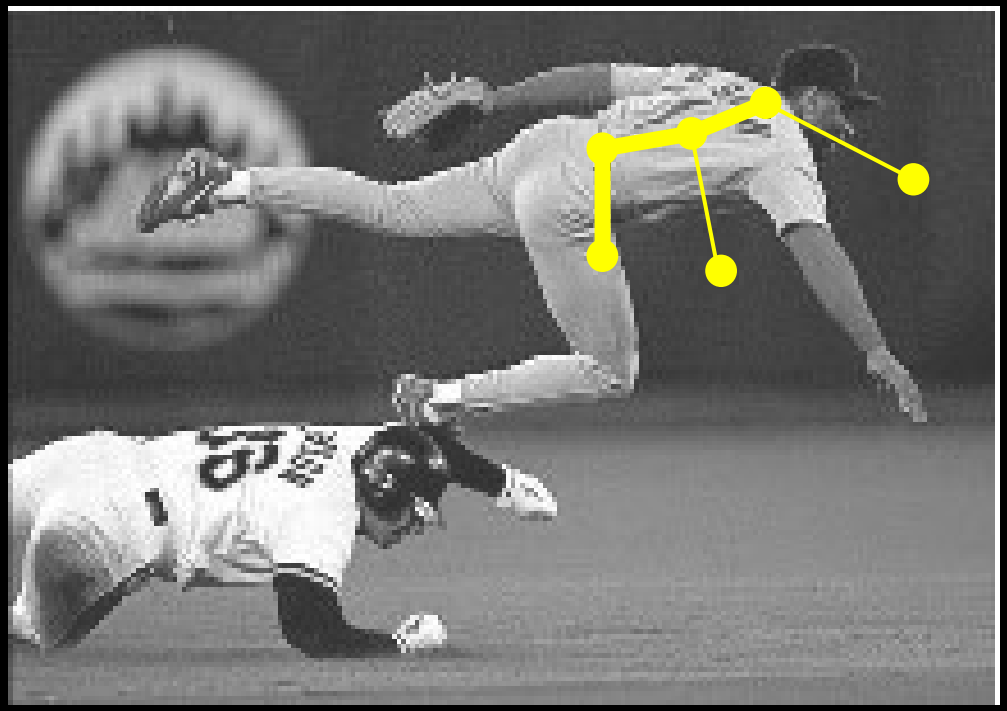
For more:
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/bench/html/108082-color.html

Contour Detection and Hierarchical Image Segmentation

Pablo Arbeláez, *Member, IEEE,* Michael Maire, *Member, IEEE,*
Charless Fowlkes, *Member, IEEE,* and Jitendra Malik, *Fellow, IEEE.*

Abstract—This paper investigates two fundamental problems in computer vision: contour detection and image segmentation. We present state-of-the-art algorithms for both of these tasks. Our contour detector combines multiple local cues into a globalization framework based on spectral clustering. Our segmentation algorithm consists of generic machinery for transforming the output of any contour detector into a hierarchical region tree. In this manner, we reduce the problem of image segmentation to that of contour detection. Extensive experimental evaluation demonstrates that both our contour detection and segmentation methods significantly outperform competing algorithms. The automatically generated hierarchical segmentations can be interactively refined by user-specified annotations. Computation at multiple image resolutions provides a means of coupling our system to recognition applications.

Exploiting global constraints: Image Segmentation as Graph Partitioning



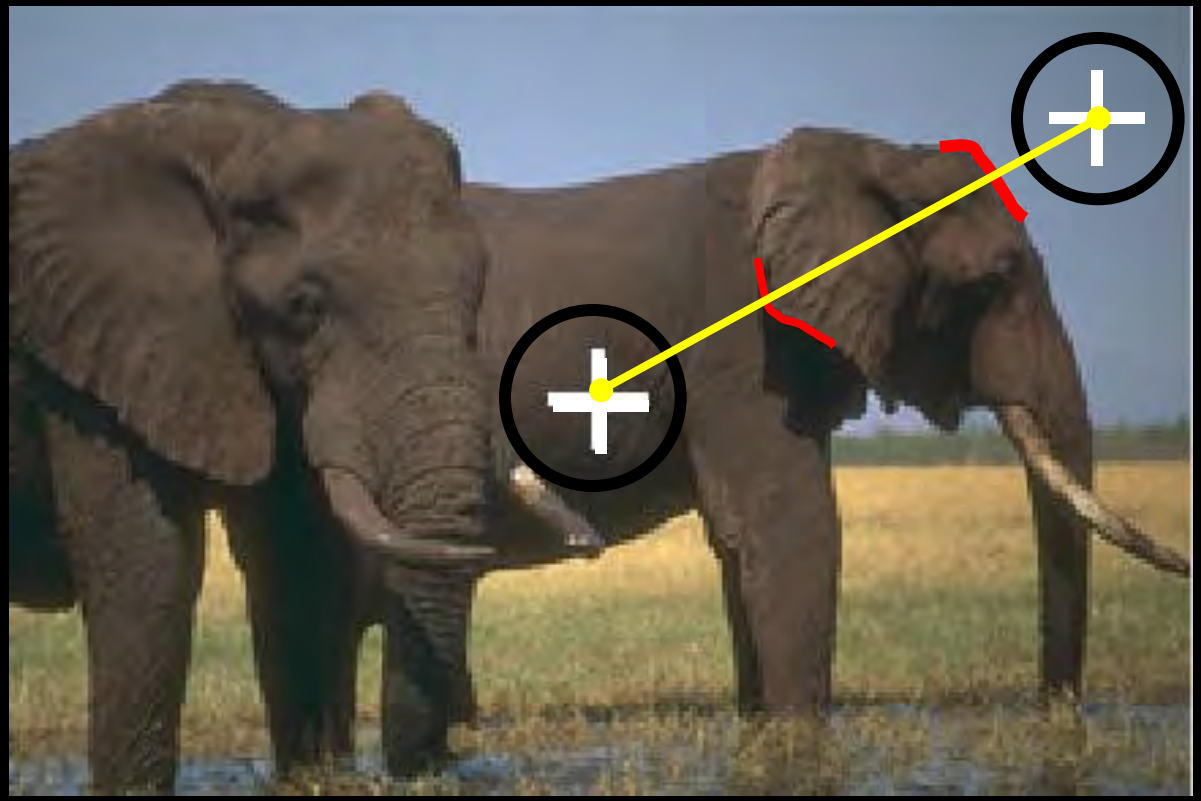
V: image pixels

E: connections between pairs of nearby pixels

Partition graph so that similarity within group is large and similarity between groups is small -- ***Normalized Cuts*** [Shi & Malik 97]

Wij small when intervening contour strong, small when weak..

Cij = max Pb(x,y) for (x,y) on line segment ij; Wij = exp (- Cij / σ



Spectral Pb

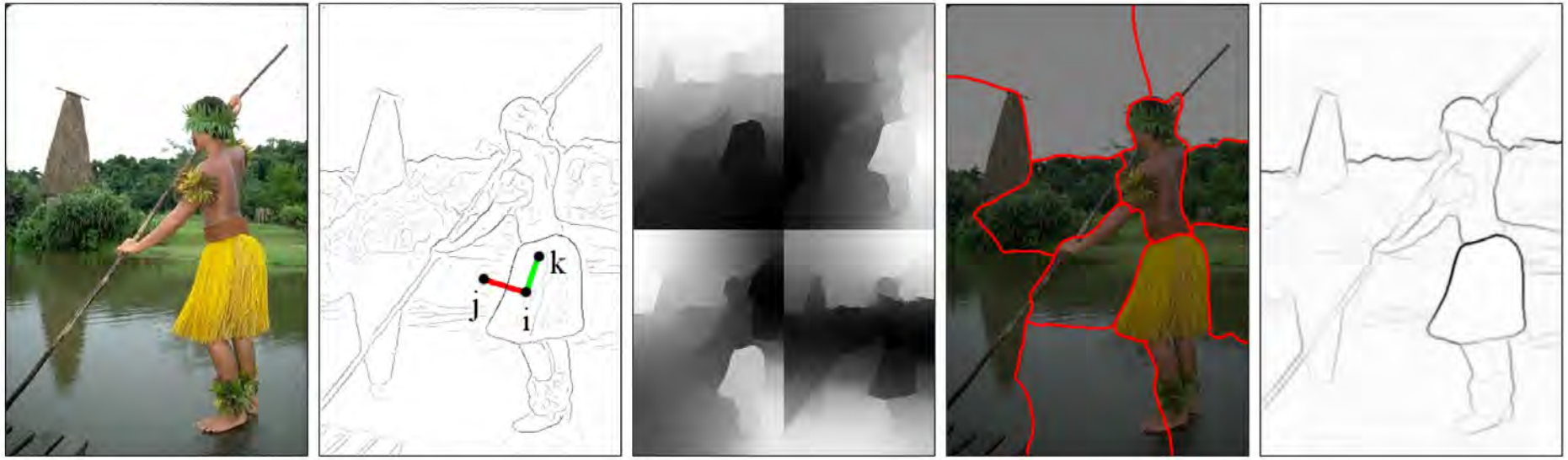
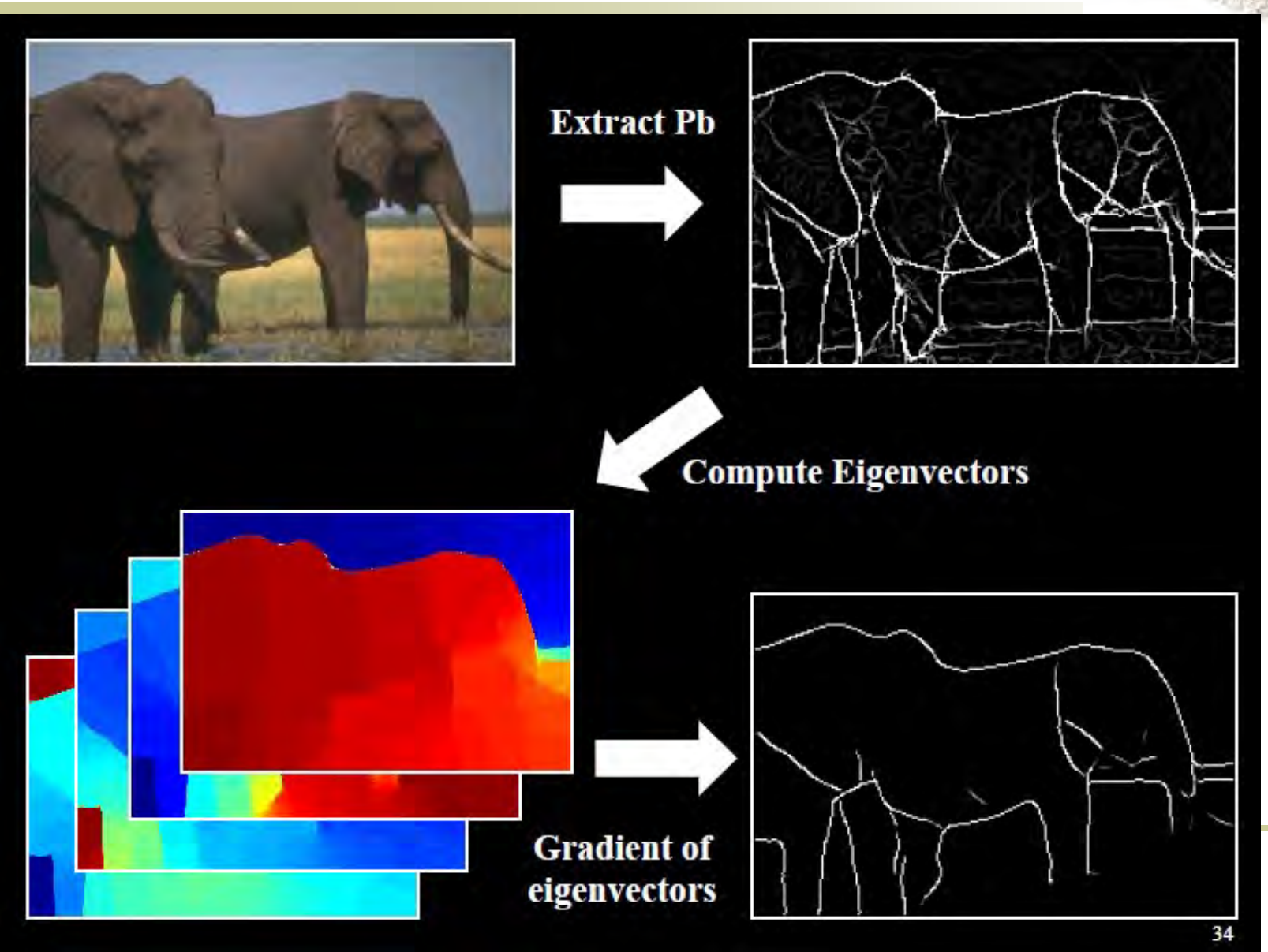


Fig. 7. **Spectral Pb.** ***Left:*** Image. ***Middle Left:*** The thinned non-max suppressed multiscale Pb signal defines a sparse affinity matrix connecting pixels within a fixed radius. Pixels i and j have a low affinity as a strong boundary separates them, whereas i and k have high affinity. ***Middle:*** First four generalized eigenvectors resulting from spectral clustering. ***Middle Right:*** Partitioning the image by running K-means clustering on the eigenvectors erroneously breaks smooth regions. ***Right:*** Instead, we compute gradients of the eigenvectors, transforming them back into a contour signal.

$$sPb(x, y, \theta) = \sum_{k=1}^{n} \frac{1}{\sqrt{\lambda_k}} \cdot \nabla_\theta \mathbf{v_k}(x, y)$$

Global pB boundary detector



Contour Detection

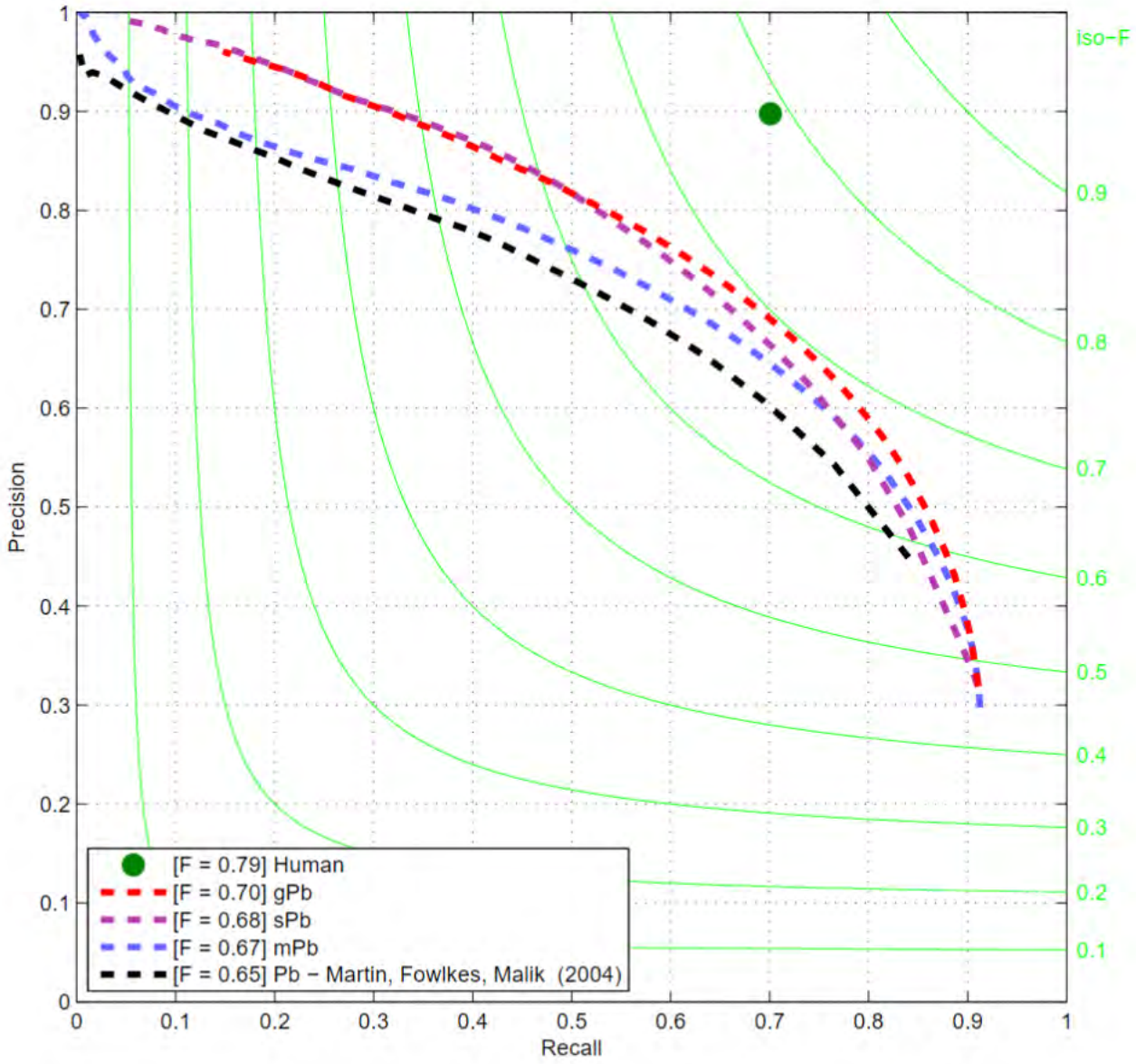
- Local and Global cues combination

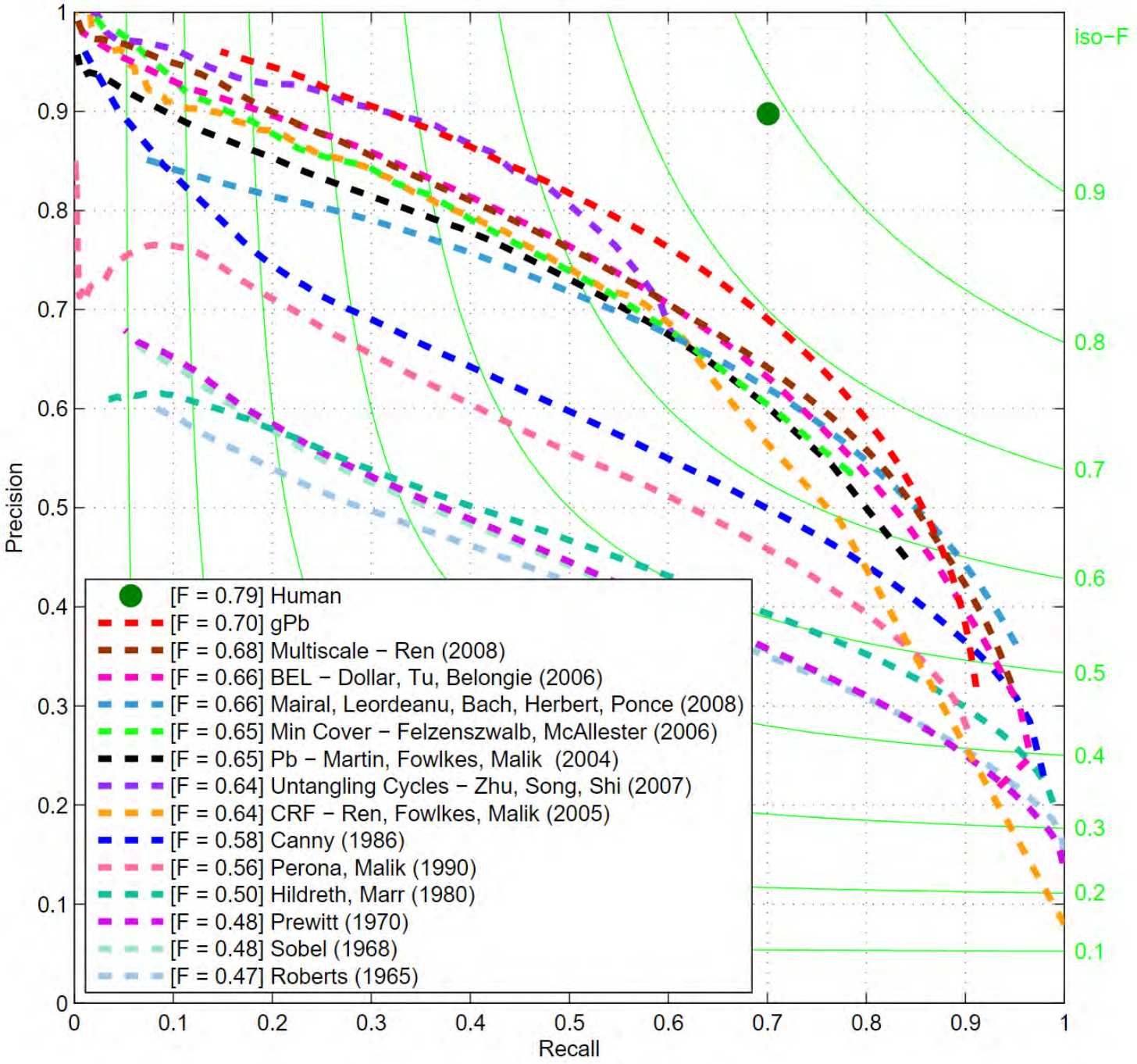
$$gPb(x, y, \theta) = \sum_s \sum_i \beta_{i,s} G_{i,\sigma(i,s)}(x, y, \theta) + \gamma \cdot sPb(x, y, \theta)$$

where s indexes scales, i indexes feature channels (brightness, color a, color b, texture), and $G_{i,\sigma(i,s)}(x, y, \theta)$ measures the histogram difference in channel i between

Global pB boundary detector

Fig. 9. **Benefits of globalization.** When compared with the local detector Pb, our detector gPb reduces clutter and completes contours. The thresholds shown correspond to the points of maximal F-measure on the curves in Figure 1.


Precision
Recall
iso-F
[F = 0.79] Human
[F = 0.70] gPb
[F = 0.68] sPb
[F = 0.67] mPb
[F = 0.65] Pb – Martin, Fowlkes, Malik (2004)


Precision
Recall
iso-F
[F = 0.79] Human
[F = 0.70] gPb
[F = 0.68] Multiscale − Ren (2008)
[F = 0.66] BEL − Dollar, Tu, Belongie (2006)
[F = 0.66] Mairal, Leordeanu, Bach, Herbert, Ponce (2008)
[F = 0.65] Min Cover − Felzenszwalb, McAllester (2006)
[F = 0.65] Pb − Martin, Fowlkes, Malik (2004)
[F = 0.64] Untangling Cycles − Zhu, Song, Shi (2007)
[F = 0.64] CRF − Ren, Fowlkes, Malik (2005)
[F = 0.58] Canny (1986)
[F = 0.56] Perona, Malik (1990)
[F = 0.50] Hildreth, Marr (1980)
[F = 0.48] Prewitt (1970)
[F = 0.48] Sobel (1968)
[F = 0.47] Roberts (1965)

Fast Edge Detection Using Structured Forests

Piotr Dollár and C. Lawrence Zitnick

Abstract—Edge detection is a critical component of many vision systems, including object detectors and image segmentation algorithms. Patches of edges exhibit well-known forms of local structure, such as straight lines or T-junctions. In this paper we take advantage of the structure present in local image patches to learn both an accurate and computationally efficient edge detector. We formulate the problem of predicting local edge masks in a structured learning framework applied to random decision forests. Our novel approach to learning decision trees robustly maps the structured labels to a discrete space on which standard information gain measures may be evaluated. The result is an approach that obtains realtime performance that is orders of magnitude faster than many competing state-of-the-art approaches, while also achieving state-of-the-art edge detection results on the BSDS500 Segmentation dataset and NYU Depth dataset. Finally, we show the potential of our approach as a general purpose edge detector by showing our learned edge models generalize well across datasets.

Index Terms—Edge detection, segmentation, structured random forests, real-time systems, visual features

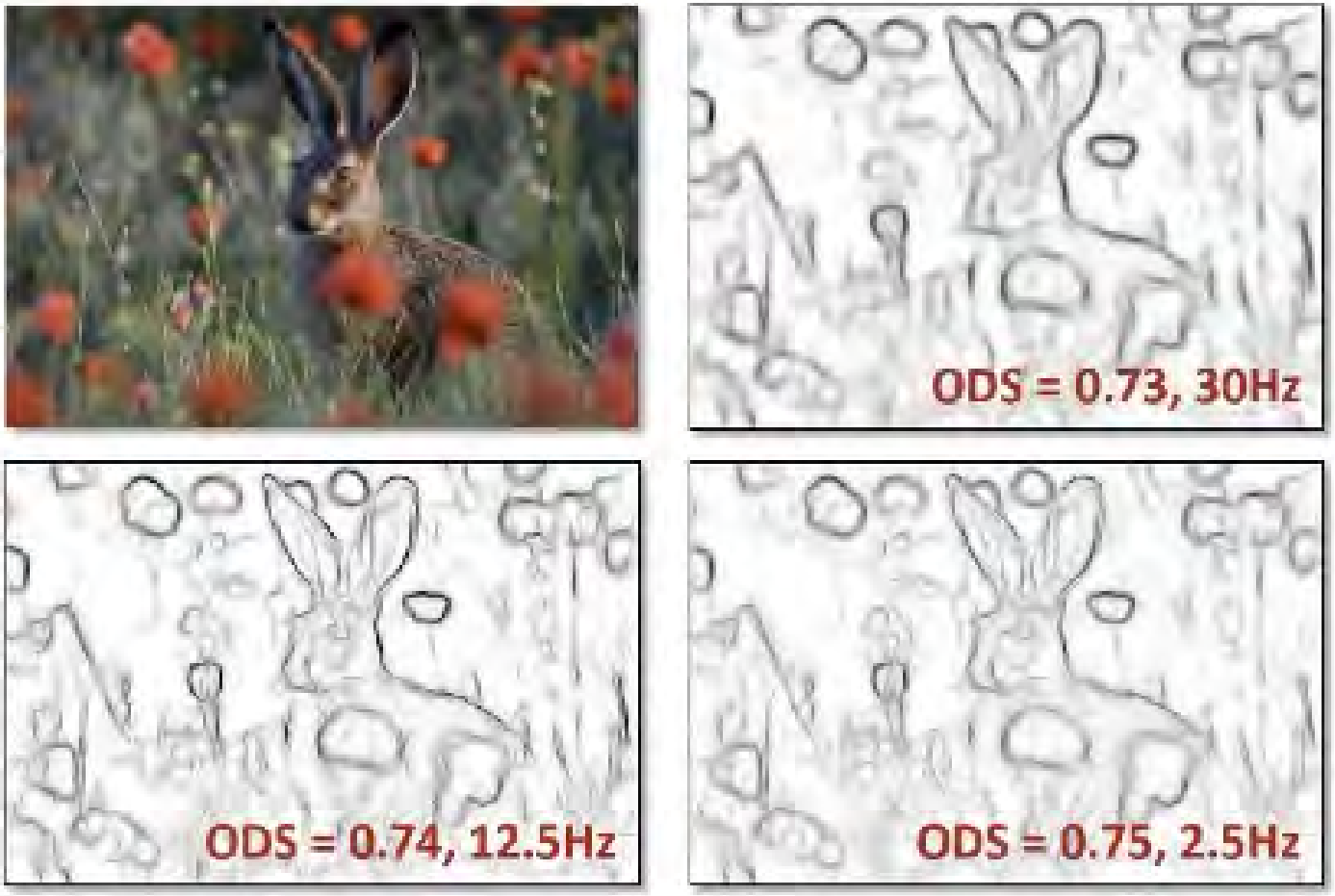


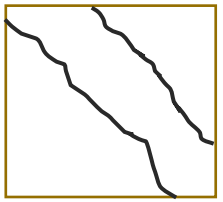
Fig. 1. Edge detection results using three versions of our Structured Edge (SE) detector demonstrating tradeoffs in accuracy vs. runtime. We obtain realtime performance while simultaneously achieving state-of-the-art results. ODS numbers were computed on BSDS [1] on which the popular gPb detector [1] achieves a score of .73. The variants shown include SE, SE+SH, and SE+MS+SH, see §4 for details.

Edge Detection with Structured Random Forests

- 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)



Boundaries in patch

http://research.microsoft.com/pubs/202540/DollarICCV13edges.pdf

Edge Detection with Structured Random Forests

- Algorithm
  1. Extract overlapping 32x32 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 16x16 region using T trained decision trees
  4. Average predictions for each pixel across all patches

Standard Decision Tree Learning

Each tree is trained independently in a recursive manner. For a given node j and training set $\mathcal{S}_j \subset \mathcal{X} \times \mathcal{Y}$, the goal is to find parameters θ_j of the split function $h(x, \theta_j)$ that result in a 'good' split of the data. This requires defining an *information gain criterion* of the form:

$$I_j = I(\mathcal{S}_j, \mathcal{S}_j^L, \mathcal{S}_j^R) \tag{2}$$

For multiclass classification ($\mathcal{Y} \subset \mathbb{Z}$) the standard definition of information gain can be used:

$$I_j = H(\mathcal{S}_j) - \sum_{k \in \{L,R\}} \frac{|S_j^k|}{|S_j|} H(S_j^k) \tag{3}$$

where $H(\mathcal{S}) = -\sum_y p_y \log(p_y)$ denotes the Shannon entropy and p_y is the fraction of elements in $\mathcal{S}$ with label y. Alternatively the Gini impurity $H(\mathcal{S}) = \sum_y p_y(1-p_y)$ has also been used in conjunction with Eqn. (3) [6].

For regression, entropy and information gain can be extended to continuous variables [11]. Alternatively, a common approach for single-variate regression ($\mathcal{Y} = \mathbb{R}$) is to minimize the variance of labels at the leaves [6]. If we write the variance as $H(S) = \frac{1}{|\mathcal{S}|}\sum_y (y-\mu)^2$ where $\mu = \frac{1}{|\mathcal{S}|}\sum_y y$, then substituting H for entropy in Eqn. (3) leads to the standard criterion for single-variate regression.

General Information Gain

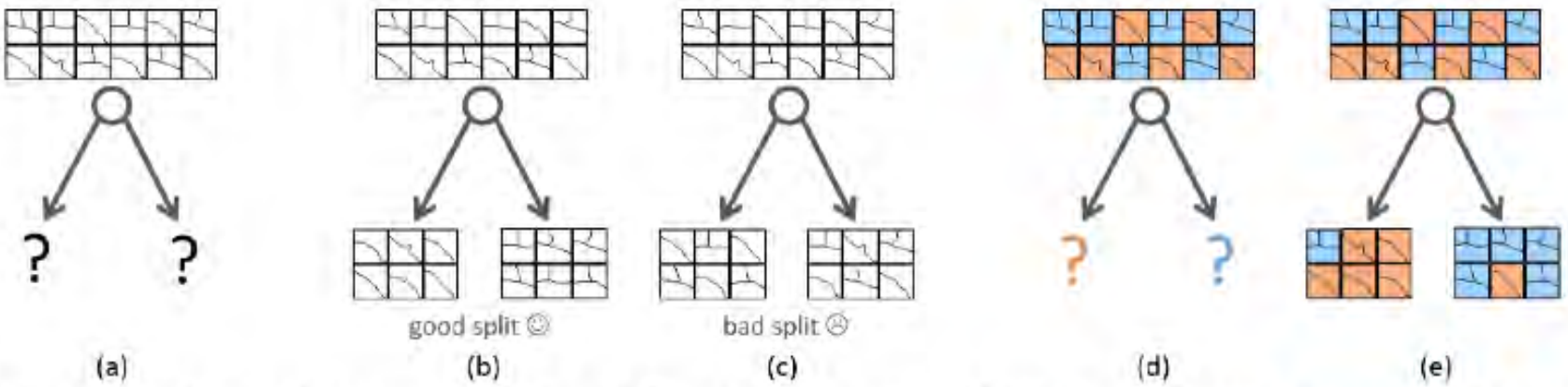
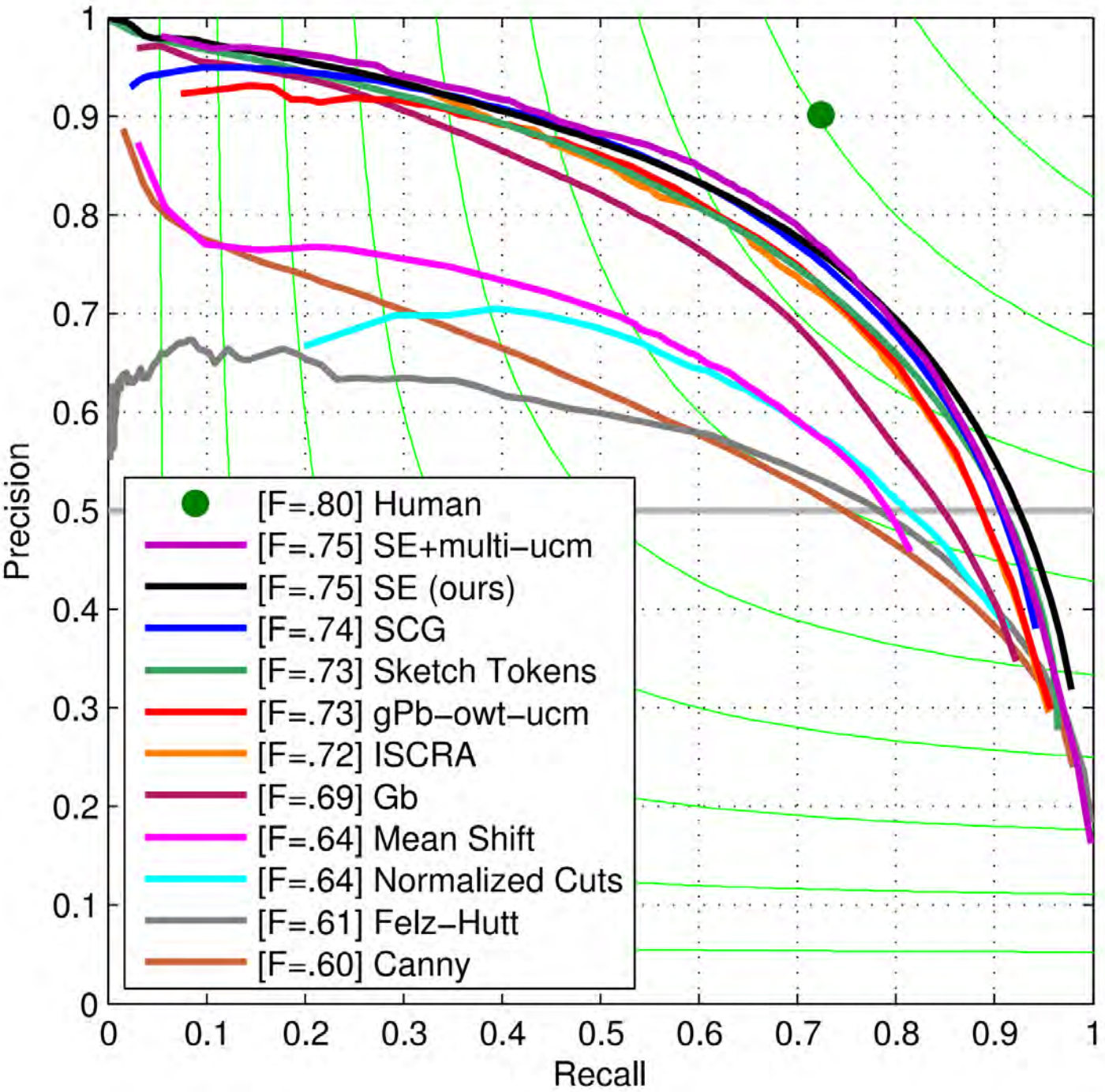


Fig. 2. Illustration of the decision tree node splits: (a) Given a set of structured labels such as segments, a splitting function must be determined. Intuitively a good split (b) groups similar segments, whereas a bad split (c) does not. In practice we cluster the structured labels into two classes (d). Given the class labels, a standard splitting criterion, such as Gini impurity, may be used (e).

Our key assumption is that for many structured output spaces, including for structured learning of edge detection, we can define a mapping of the form:

$$\Pi : \mathcal{Y} \rightarrow \mathcal{Z} \qquad (4)$$

We map a set of structured labels $y \in \mathcal{Y}$ into a discrete set of labels $c \in \mathcal{C}$, where $\mathcal{C} = \{1, \ldots, k\}$, such that labels with similar z are assigned to the same discrete label c, see


Precision
Recall
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
[F=.80] Human
[F=.75] SE+multi–ucm
[F=.75] SE (ours)
[F=.74] SCG
[F=.73] Sketch Tokens
[F=.73] gPb–owt–ucm
[F=.72] ISCRA
[F=.69] Gb
[F=.64] Mean Shift
[F=.64] Normalized Cuts
[F=.61] Felz–Hutt
[F=.60] Canny

Edge Detection with Structured Random Forests

Results

BSDS 500

	ODS	OIS	AP	FPS
Human	.80	.80	-	-
Canny	.60	.64	.58	15
Felz-Hutt [11]	.61	.64	.56	10
Hidayat-Green [16]	.62†	-	-	20
BEL [9]	.66†	-	-	1/10
gPb + GPU [6]	.70†	-	-	1/2‡
gPb [1]	.71	.74	.65	1/240
gPb-owt-ucm [1]	.73	**.76**	.73	1/240
Sketch tokens [21]	.73	.75	**.78**	1
SCG [31]	**.74**	**.76**	.77	1/280
SE-SS, T=1	.72	.74	.77	**60**
SE-SS, T=4	.73	.75	.77	30
SE-MS, T=4	**.74**	**.76**	**.78**	6

NYU Depth dataset edges

	ODS	OIS	AP	FPS
gPb [1] (rgb)	.51	.52	.37	1/240
SCG [31] (rgb)	.55	.57	.46	1/280
SE-SS (rgb)	.58	.59	.53	**30**
SE-MS (rgb)	**.60**	**.61**	**.56**	6
gPb [1] (depth)	.44	.46	.28	1/240
SCG [31] (depth)	.53	.54	.45	1/280
SE-SS (depth)	.57	.58	.54	**30**
SE-MS (depth)	**.58**	**.59**	**.57**	6
gPb [1] (rgbd)	.53	.54	.40	1/240
SCG [31] (rgbd)	.62	.63	.54	1/280
SE-SS (rgbd)	.62	.63	.59	**25**
SE-MS (rgbd)	**.64**	**.65**	**.63**	5

Holistically-Nested Edge Detection

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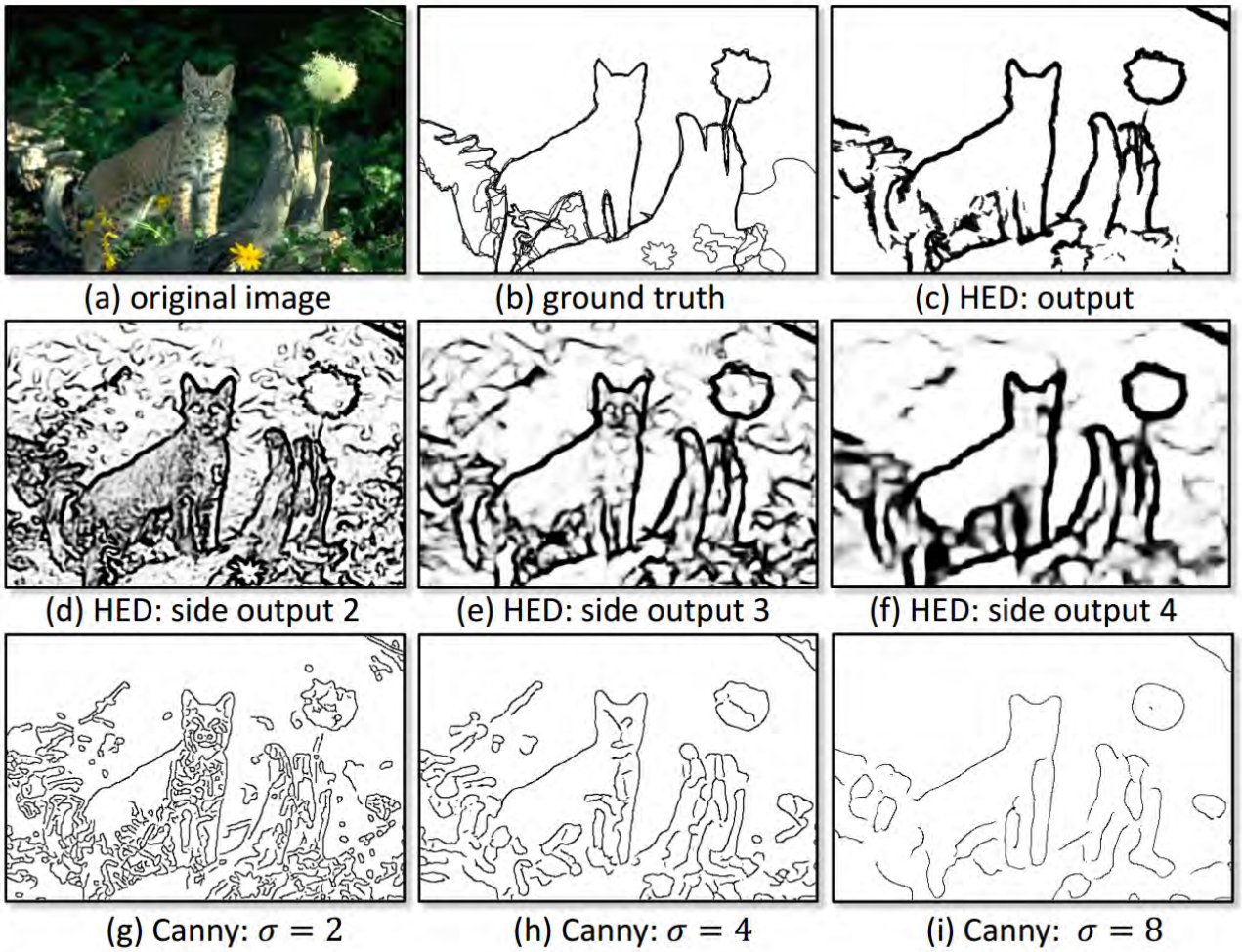


Figure 1. Illustration of the proposed HED algorithm. In the first row: (a) shows an example test image in the BSD500 dataset [28]; (b) shows its corresponding edges as annotated by human subjects; (c) displays the HED results. In the second row: (d), (e), and (f), respectively, show side edge responses from layers 2, 3, and 4 of our convolutional neural networks. In the third row: (g), (h), and (i), respectively, show edge responses from the Canny detector [4] at the scales $\sigma = 2.0$, $\sigma = 4.0$, and $\sigma = 8.0$. HED shows a clear advantage in consistency over Canny.

Holistically nested edge detection

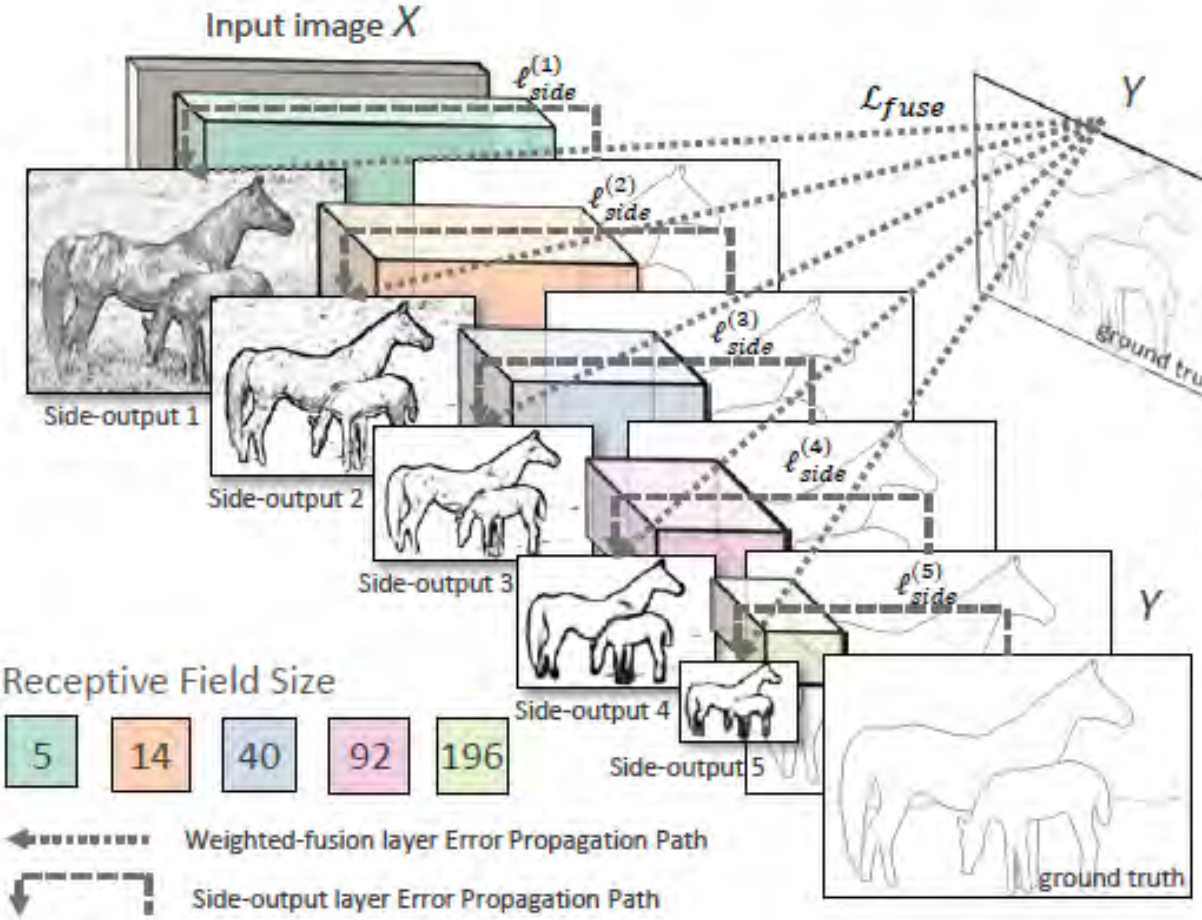
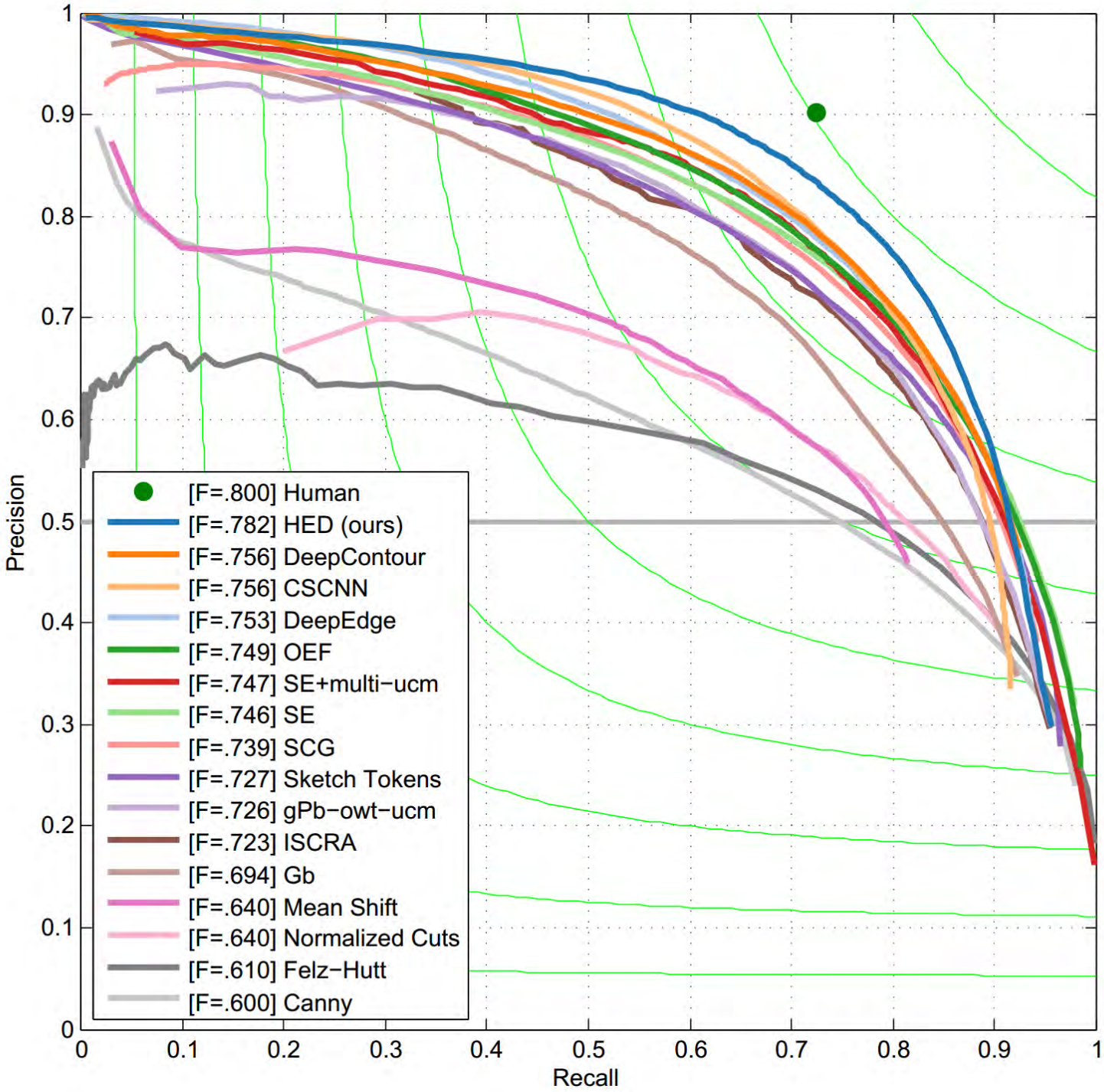


Table 4. Results on BSDS500. ∗BSDS300 results,†GPU time

	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

https://arxiv.org/pdf/1504.06375.pdf


Precision
Recall
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
[F=.800] Human
[F=.782] HED (ours)
[F=.756] DeepContour
[F=.756] CSCNN
[F=.753] DeepEdge
[F=.749] OEF
[F=.747] SE+multi−ucm
[F=.746] SE
[F=.739] SCG
[F=.727] Sketch Tokens
[F=.726] gPb−owt−ucm
[F=.723] ISCRA
[F=.694] Gb
[F=.640] Mean Shift
[F=.640] Normalized Cuts
[F=.610] Felz−Hutt
[F=.600] Canny

State of edge detection

- Local edge detection is mostly solved
  - Intensity gradient, color, texture
  - HED on BSDS 500 is near human performance
- Some room for improvement by taking advantage of higher-level knowledge (e.g., objects)
- Still hard to produce all objects within a small number of regions

Finding straight lines

Finding line segments using connected components

1. Compute canny edges
   - Compute: gx, gy (DoG in x,y directions)
   - Compute: theta = atan(gy / gx)
2. Assign each edge to one of 8 directions
3. For each direction d, get edgelets:
   - find connected components for edge pixels with directions in {d-1, d, d+1}
4. Compute straightness and theta of edgelets using eig of x,y 2nd moment matrix of their points

$$\mathbf{M} = \begin{bmatrix} \sum (x-\mu_x)^2 & \sum (x-\mu_x)(y-\mu_y) \\ \sum (x-\mu_x)(y-\mu_y) & \sum (y-\mu_y)^2 \end{bmatrix} \qquad [v,\lambda] = \text{eig}(\mathbf{M})$$

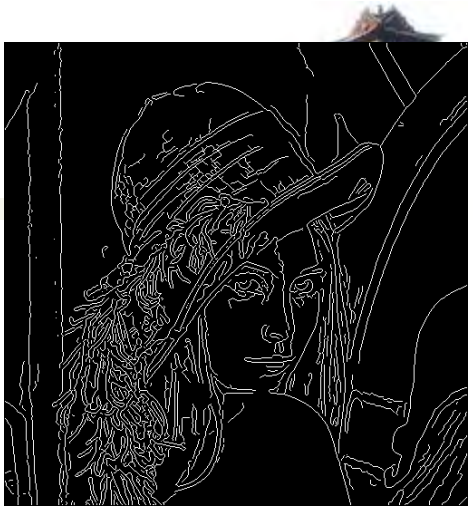
Larger eigenvector

$$\theta = \text{atan}\,2(v(2,2), v(1,2))$$

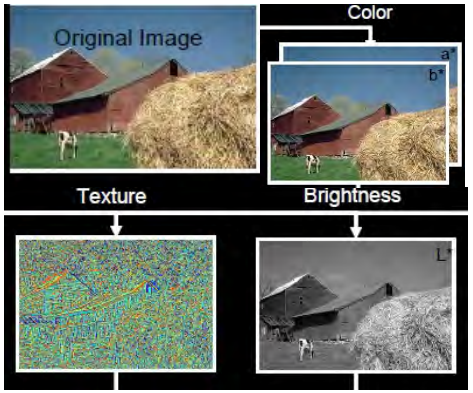
$$conf = \lambda_2 / \lambda_1$$

5. Threshold on straightness, store segment

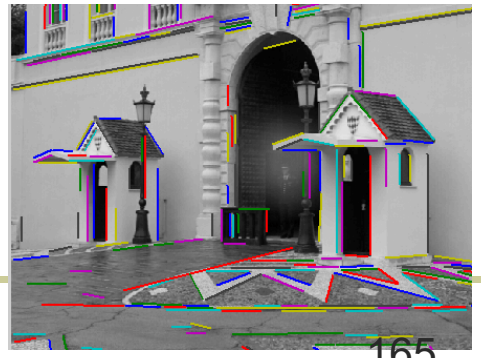
Things to remember



- Canny edge detector = smooth → derivative → thin → threshold → link



- Pb: learns weighting of gradient, color, texture differences
  - More recent learning approaches give at least as good accuracy and are faster



- Straight line detector = canny + gradient orientations → orientation binning → linking → check for straightness