# Contours and Regions

Pablo Arbeláez
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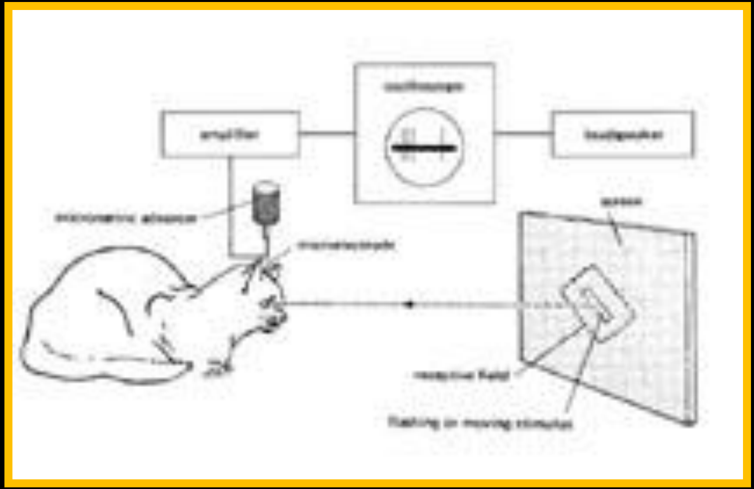
# I. HISTORICAL MOTIVATION

# Some Computer Vision "Prehistory"

- Hubel and Wiesel (1981 Nobel Price winners):



*Selective response: Physiological evidence for the importance of oriented edges in early visual perception*


- Hubel, D. H. & T. N. Wiesel, Receptive Fields Of Single Neurons In The Cat's Striate Cortex, Journal of Physiology, (I959) I48, 574-59I.
- Hubel, D. H. & T. N. Wiesel. Receptive Fields, Binocular Interaction And Functional Architecture In The Cat's Visual Cortex, Journal of Physiology, (1962), 160, pp. 106-154, With 2 plates and 20 text-figures.

# Some Computer Vision "Prehistory"

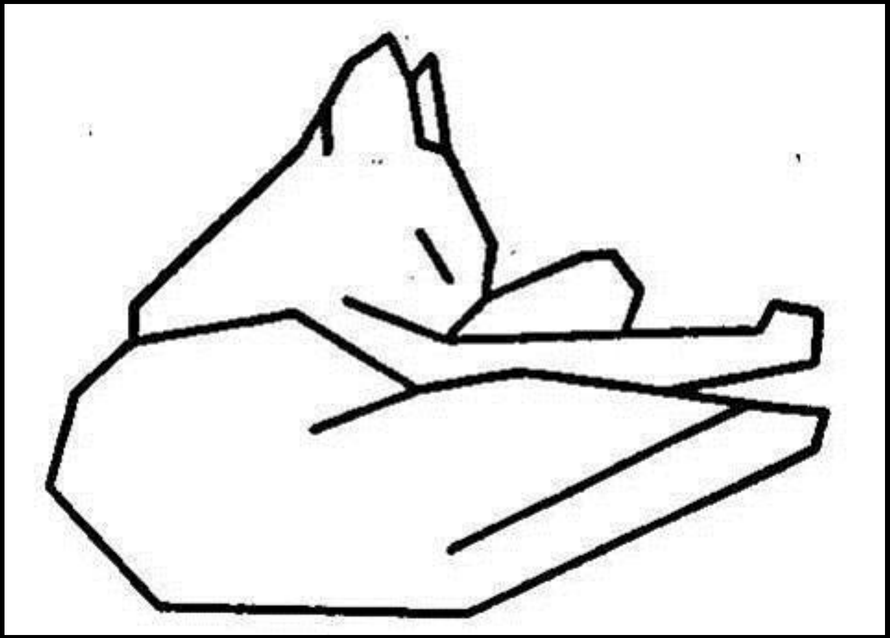
## Hubel and Wiesel's eureka moment

http://www.youtube.com/watch?v=IOHayh06LJ4

*In memoriam: the poor cat*

# Some Computer Vision "Prehistory"

- Attneave's sleeping cat (1954)



*Humans can interpret visual information even from simplified line drawings*

- Attneave, F. (1954). Some Informational Aspects Of Visual Perception. Psychological Review, 61, 183-193.

# First Computer Vision Thesis

**Lawrence Roberts (MIT - 1963)**

*Machine Perception Of Three-Dimensional Solids*

ABSTRACT:
*“(…)* A computer program has been written which can process a photograph into a line drawing , transform the line drawing into a three-dimensional representation, and ,finally, display the three-dimensional structure with all the hidden lines removed, from any point of view. The 2-D to 3-D construction and 3-D to 2-D display processes are sufficiently general to handle most collections of planar-surfaced objects and provide a valuable starting point for future investigation of computer-aided three-dimensional systems.”

http://www.packet.cc/files/mach-per-3D-solids.html

# After 30 Years of Intensive Research…

## Edge Detection

- Sobel (1968)
- Prewitt (1970)
- Hildreth, Marr (1980)
- Canny (1986)
- Perona, Malik (1990)
- …
- …
- …

## Image Segmentation

- Horowitz, Pavlidis (1974)
- Beucher, Lantuéjoul (1979)
- Mumford, Shah (1989)
- Wu, Leahy (1993)
- …
- …
- …

Today it remains an active field of research:
(Google Scholar search with exact expression in article title)

8,290 results

17,200 results

# Example of segmentation papers from the 1980s: Mumford and Shah's formulation

- The segmentation **u** of an observed image **u0** is given by the minimization of the functional:

$$\mathcal{F}(u, C) = \int_{\Omega} (u - u_0)^2 dx + \mu \int_{\Omega \setminus C} |\nabla(u)|^2 dx + \nu |C|$$

Data fidelity

Smoothness

Regularization

- D. Mumford and J. Shah, "Optimal approximations by piecewise smooth functions, and associated variational problems," Communications on Pure and Applied Mathematics, pp. 577–684, 1989.

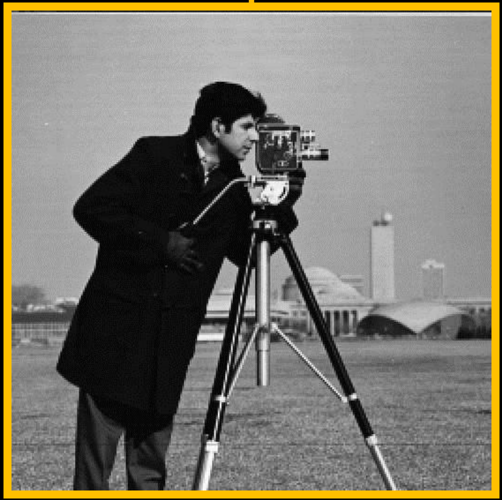
# Folk's Wisdom circa 1995

## Edge Detection

*"Canny is as good as you get"*

## Image Segmentation

*"Segmentation is an ill-posed problem"*



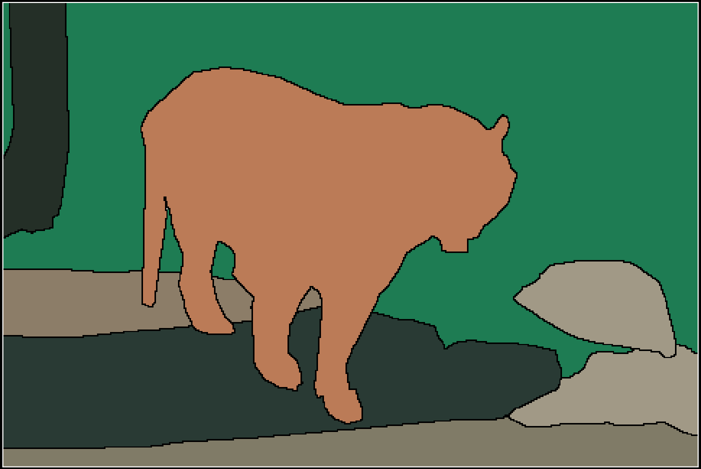
Lack of data to study the problem on empirical grounds.

# II. RECENT RESEARCH

# Contour Detection and Image Segmentation

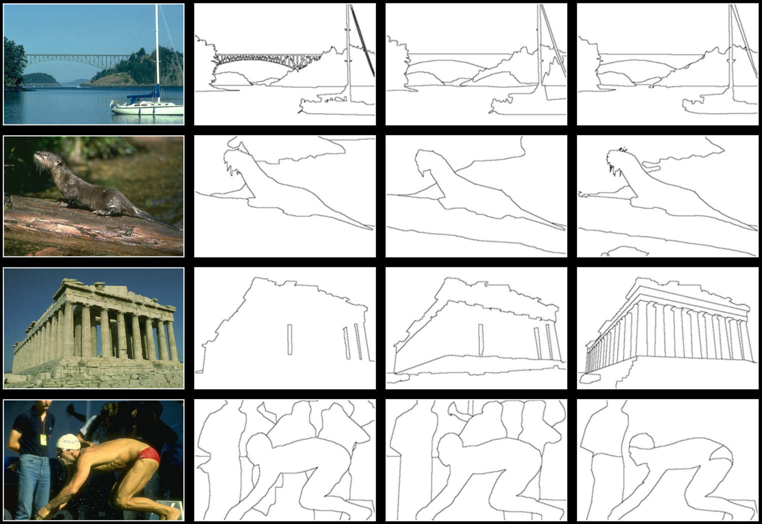
Pablo Arbeláez[1], Michael Maire[2], Charless Fowlkes[3], and Jitendra Malik[1]

[1]University of California at Berkeley
[2]California Institute of Technology
[3]University of California at Irvine



# How to train/test?

# Berkeley Segmentation Dataset



D. Martin, C. Fowlkes, D. Tal, and J. Malik. "A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics", ICCV, 2001

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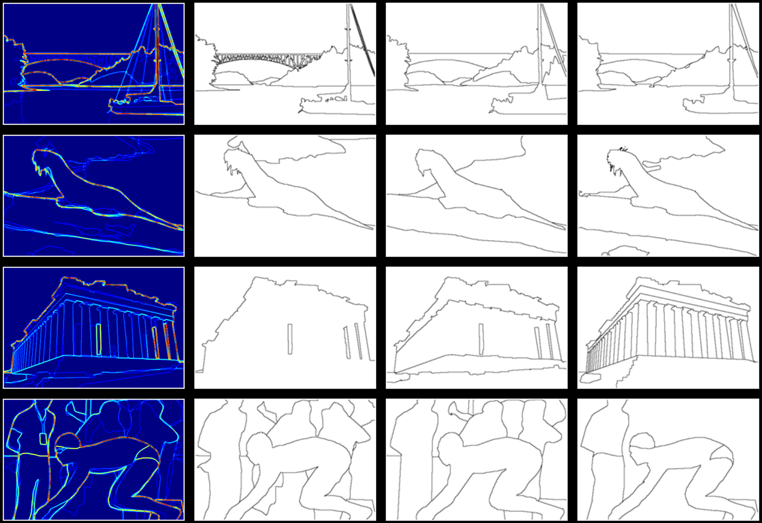
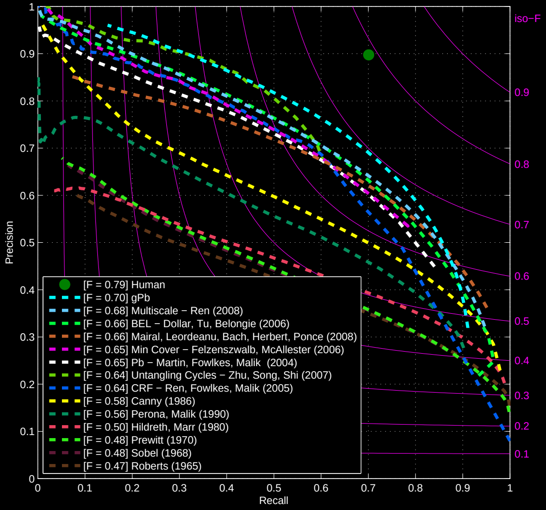


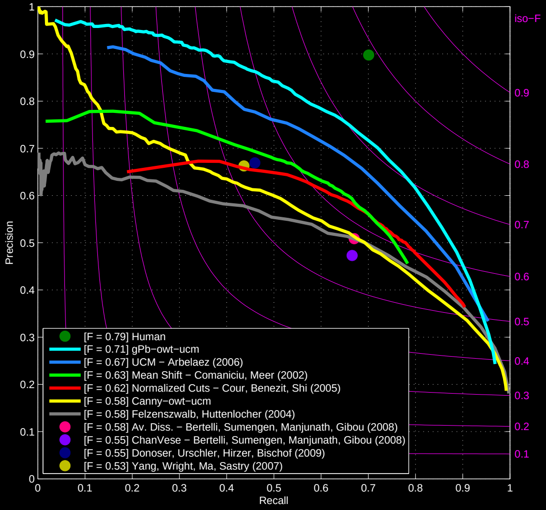
D. Martin, C. Fowlkes, D. Tal, and J. Malik. "A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics", ICCV, 2001

# Results: Contours




M. Maire, P. Arbeláez, C. Fowlkes, and J. Malik. "Using Contours to Detect and Localize Junctions in Natural Images", CVPR, 2008

# Results: Segmentation




P. Arbeláez, M. Maire, C. Fowlkes, and J. Malik.
“From Contours to Regions: An Empirical Evaluation”, CVPR, 2009

# Overview

# Overview

- Contour Detection
  - Multiscale Local Cues
  - Globalization

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- Contours $\longrightarrow$ Hierarchical Segmentation
  - Oriented Watershed Transform (OWT)
    (Contours $\longrightarrow$ Initial Regions)
  - Ultrametric Contour Map (UCM)
    (Initial Regions $\longrightarrow$ Hierarchy)

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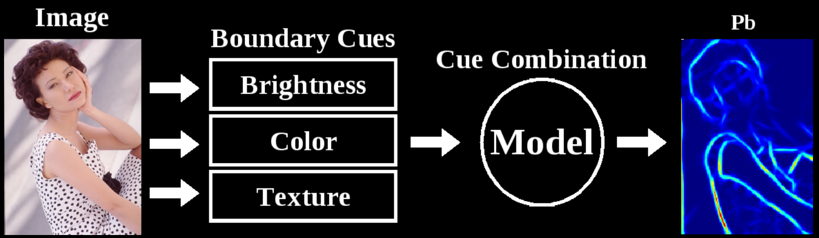
- Interactive Segmentation
- Multiscale Object Analysis

# Contour Detection

# Local Cues for Contour Detection

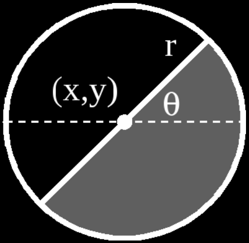
Estimate the posterior probability of a boundary $Pb(x, y, \theta)$



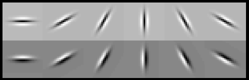

D. Martin, C. Fowlkes, and J. Malik. "Learning to Detect Natural Image Boundaries using Local Brightness, Color and Texture Cues", TPAMI 2004.

# Local Cues for Contour Detection

- 1976 CIE L*a*b* colorspace
- Brightness Gradient $BG(x, y, r, \theta)$
  Difference of L* distributions
- Color Gradient $CG(x, y, r, \theta)$
  Difference of a*b* distributions




- Texture Gradient $TG(x, y, r, \theta)$
  Difference of distributions of V1-like filter responses

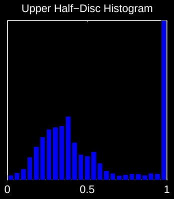


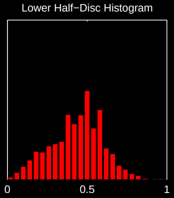
We combine these cues across multiple scales ($r$)

# Local Cues for Contour Detection

L a b textons

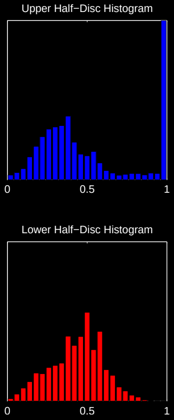
# Local Cues for Contour Detection

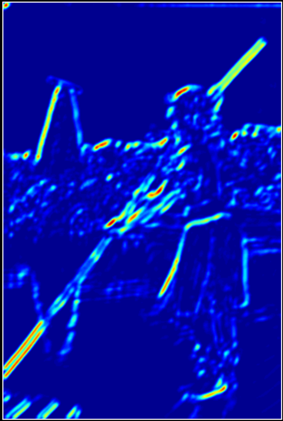



L

# Local Cues for Contour Detection

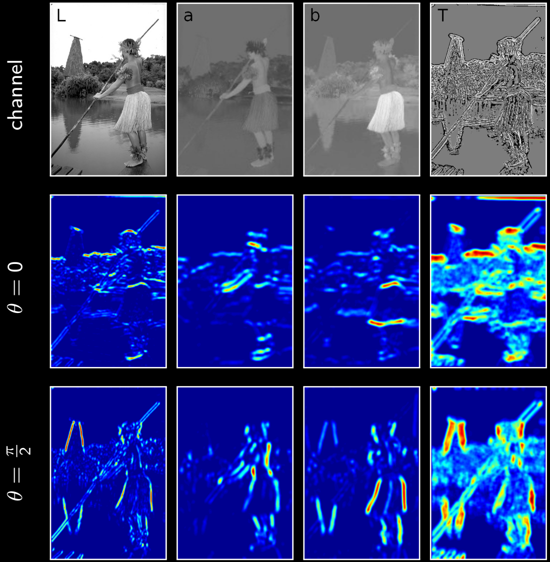


L

$$G(x, y, \theta = \frac{\pi}{4})$$

# Local Cues for Contour Detection



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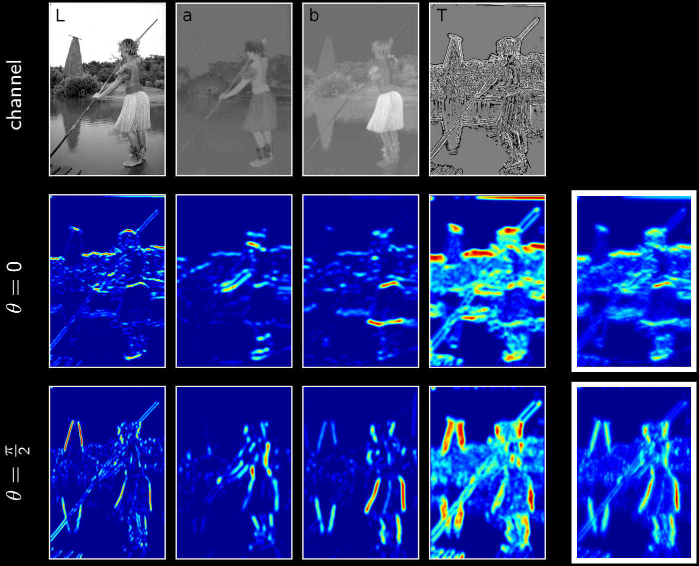

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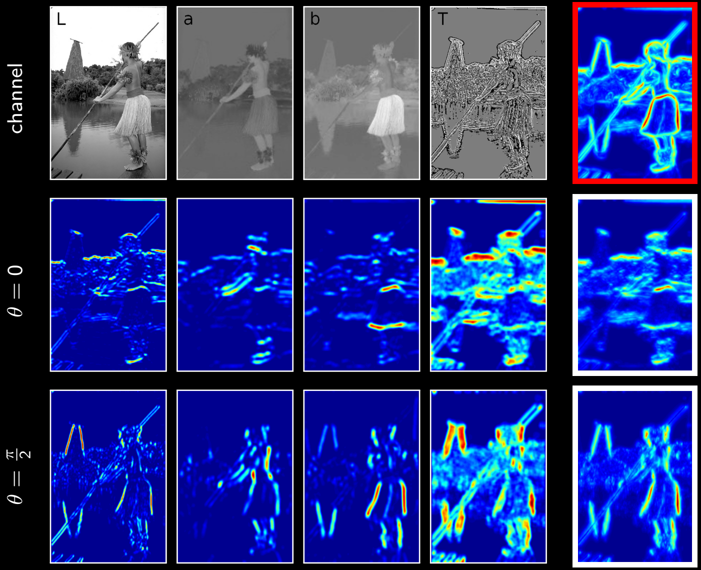

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Build a weighted graph $G = (V, E, W)$ from the image

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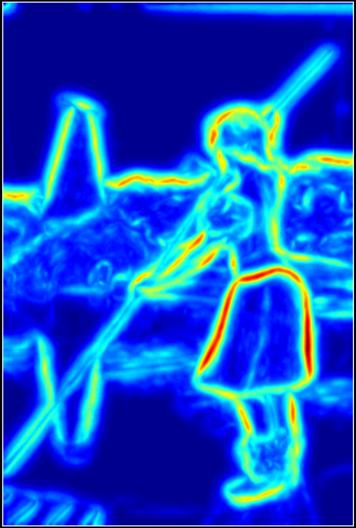
- Nonmax suppression



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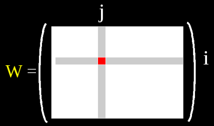
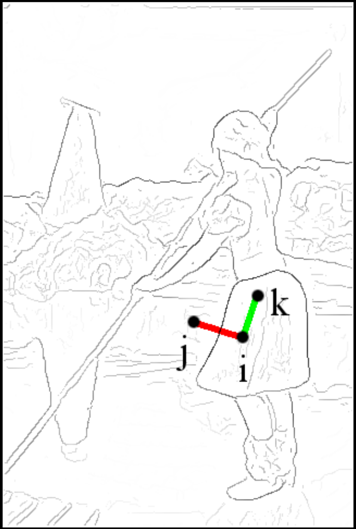
- Define $W$ using Intervening Contour




$(i, j)$ low affinity



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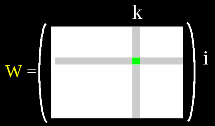
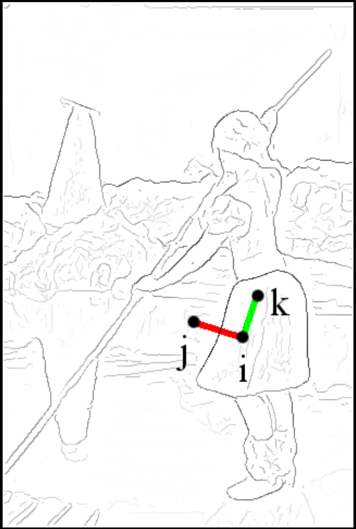



$(i, k)$ high affinity



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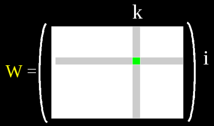


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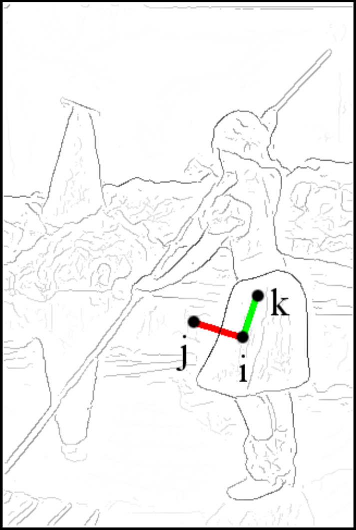
- Normalized Cuts
  [Shi & Malik 1997]



# Normalized Cuts

- Graph $G = (V, E, W)$
- Split into $A$, $B$ disjoint, $A \cup B = V$

J. Shi and J. Malik. "Normalized Cuts and Image Segmentation", PAMI, 2000.

# Normalized Cuts

- Graph $G = (V, E, W)$
- Split into $A$, $B$ disjoint, $A \cup B = V$

$$cut(A, B) = \sum_{u \in A, v \in B} w(u, v) \qquad assoc(A, V) = \sum_{u \in A, v \in V} w(u, v)$$

$$Ncut(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)}$$

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- General case: partition using smallest eigenvectors of

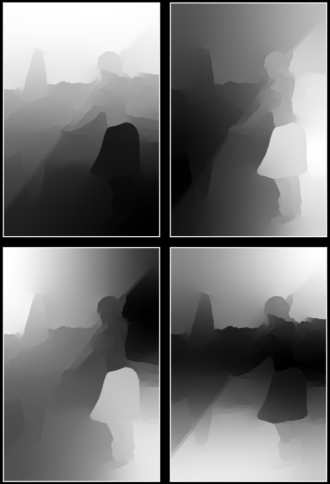
$$(D - W)v = \lambda D v$$

where $D_{ii} = \sum_j W_{ij}$

J. Shi and J. Malik. "Normalized Cuts and Image Segmentation", PAMI, 2000.

# Do NOT Cluster Eigenvectors!

Image

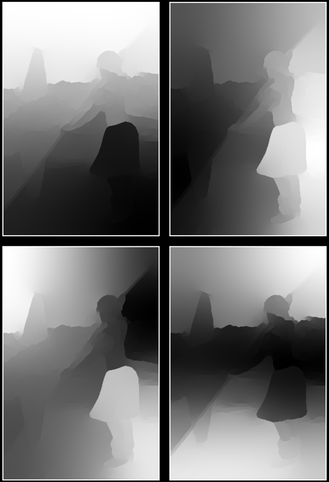


Eigenvectors

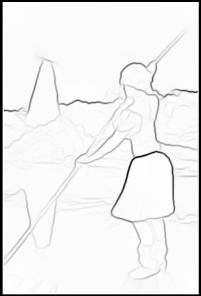
Clustering eigenvector values leads to artifacts on uniform regions.

# Eigenvectors Carry Contour Information

Image

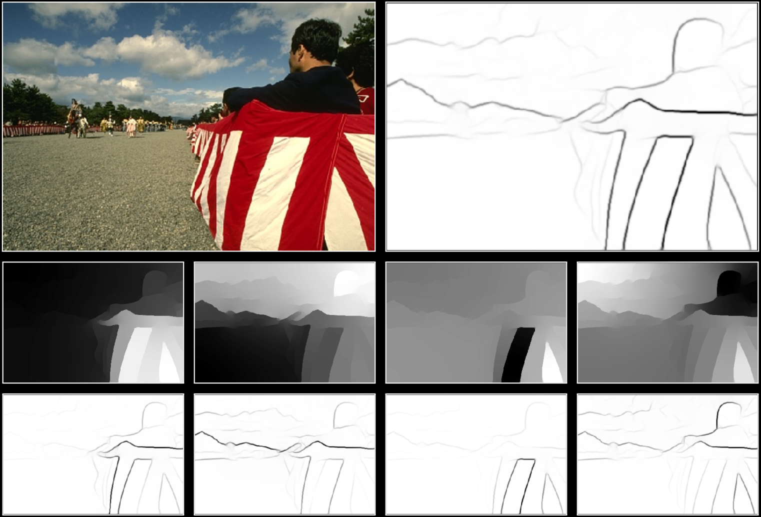


Eigenvectors



We use the gradients of eigenvectors rather than their values.

# Eigenvectors Carry Contour Information



Gradients of eigenvectors indicate salient contours in the image.

# Contour Detection

- Multiscale Brightness, Color, Texture Gradients:

$$mPb(x, y, \theta) = \sum_{s} \sum_{i} \alpha_{i,s} G_{i,\sigma(s)}(x, y, \theta)$$

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$$mPb(x,y,\theta) = \sum_s \sum_i \alpha_{i,s} G_{i,\sigma(s)}(x,y,\theta)$$

- Gradients of Eigenvectors:

$$sPb(x,y,\theta) = \sum_k \frac{1}{\sqrt{\lambda_k}} \cdot \nabla_\theta v_k(x,y)$$

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- Global Probability of Boundary:

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

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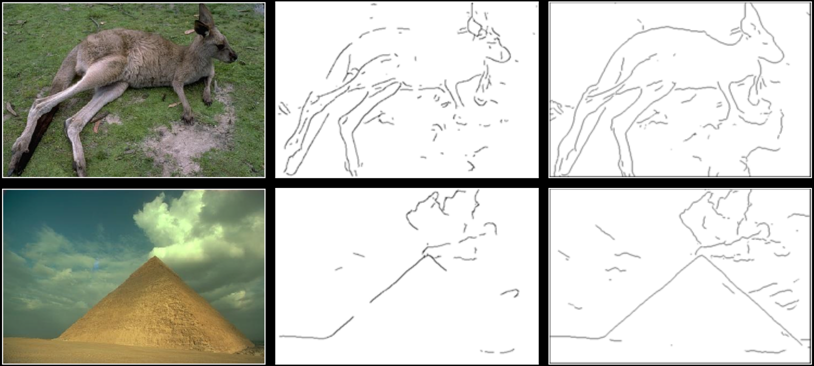
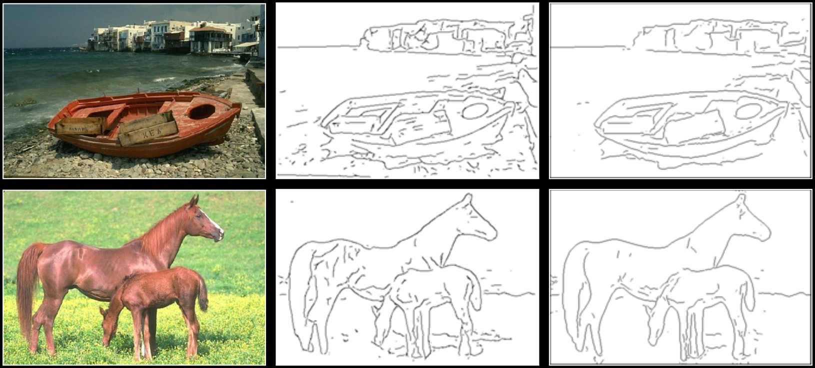
Weights learned from training data

# Benefits of Globalization



Thresholded *Pb* Thresholded *gPb*

# Benefits of Globalization



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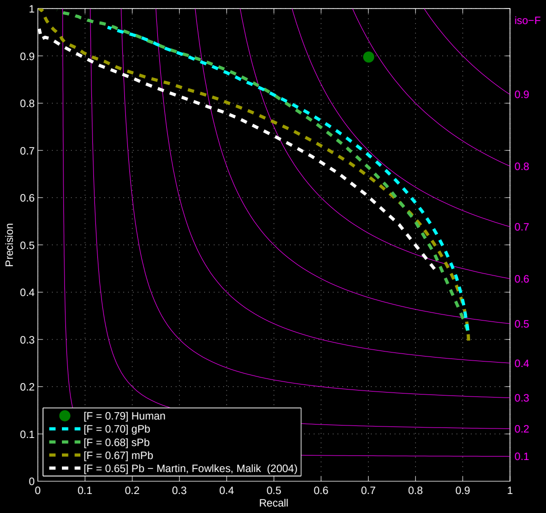

# Contours to Hierarchical Regions

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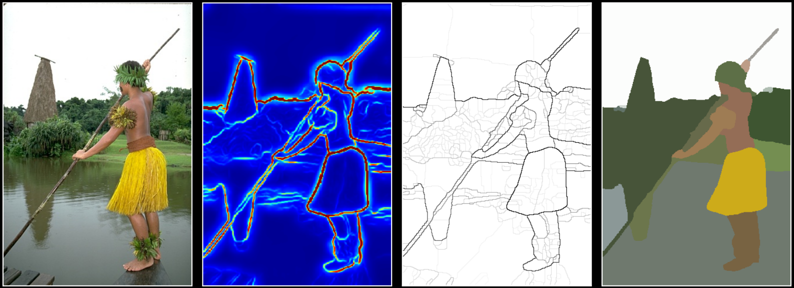
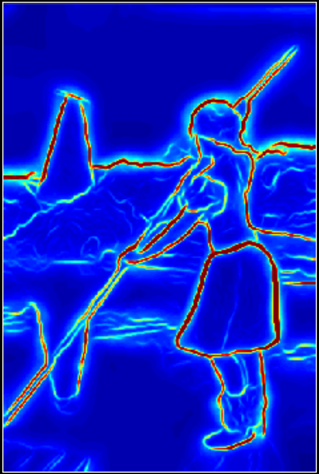


*pb* OWT-UCM Segmentation

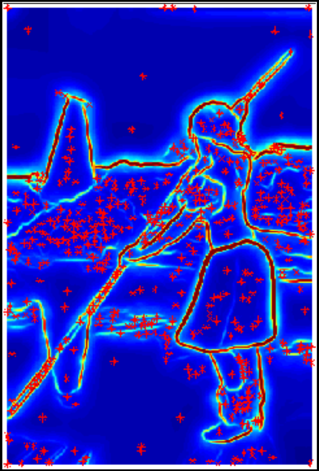
# Watershed Transform

- Compute $pb(x, y) = \max_{\theta} pb(x, y, \theta)$



# Watershed Transform

- Compute $pb(x, y) = \max_\theta pb(x, y, \theta)$
- Seed locations are regional minima of $pb(x, y)$



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- Compute $pb(x, y) = \max_\theta pb(x, y, \theta)$
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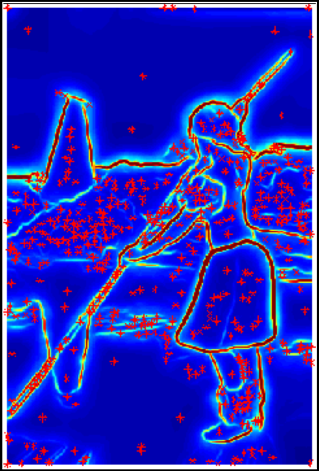

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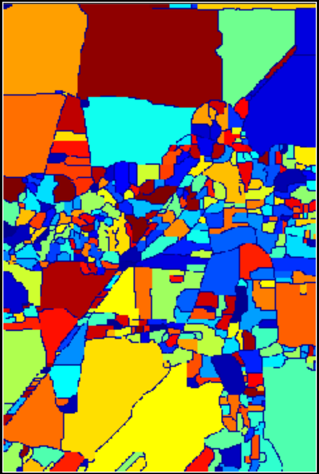
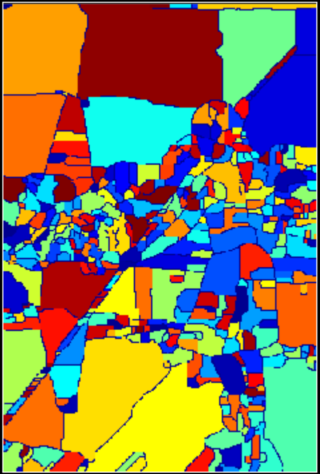
- Catchment basins $\mathcal{P}_0$ are regions

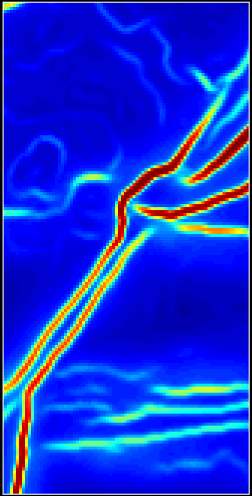


# Watershed Transform

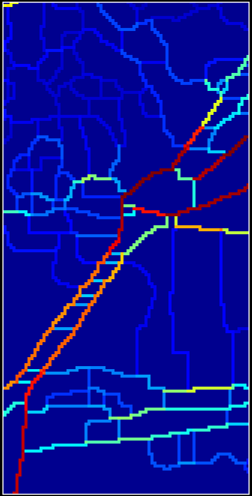
- Compute $pb(x, y) = \max_\theta pb(x, y, \theta)$
- Seed locations are regional minima of $pb(x, y)$
- Apply watershed transform
- Catchment basins $\mathcal{P}_0$ are regions
- Arcs $\mathcal{K}_0$ are boundaries



# Oriented Watershed Transform (OWT)

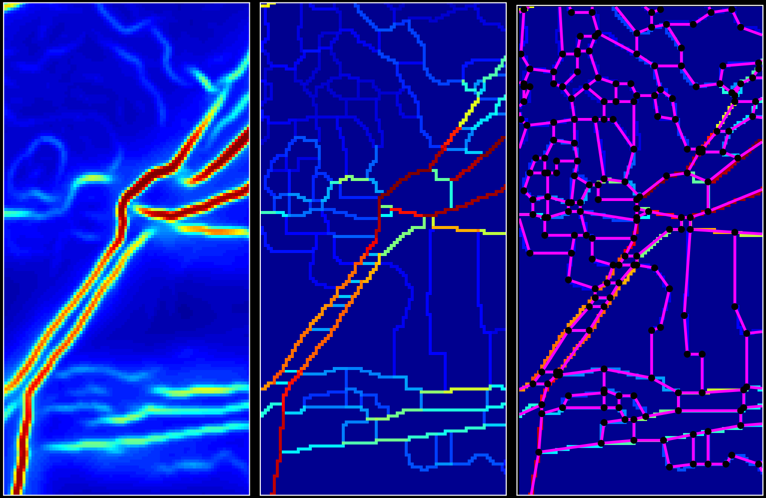


$pb(x, y)$



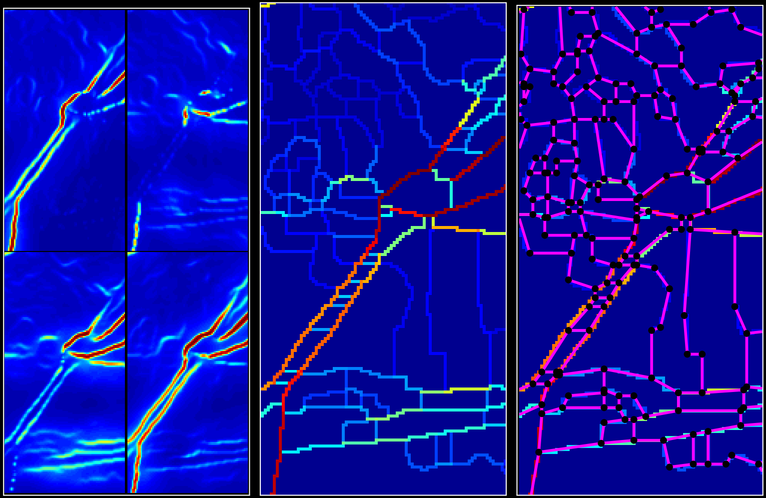
Watershed

# Oriented Watershed Transform (OWT)



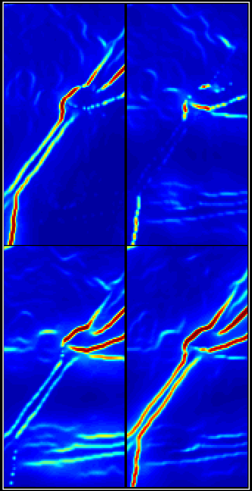
$pb(x, y)$ Watershed Subdivision

# Oriented Watershed Transform (OWT)

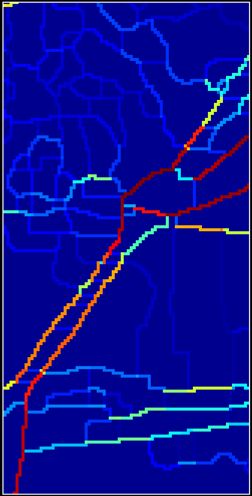


$pb(x, y, \theta)$ Watershed Subdivision

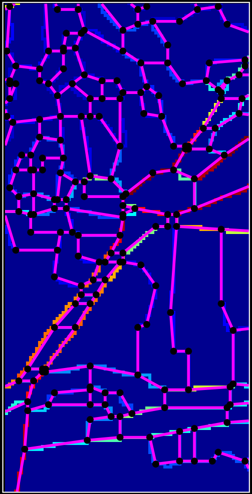
# Oriented Watershed Transform (OWT)



$pb(x, y, \theta)$



OWT



Subdivision

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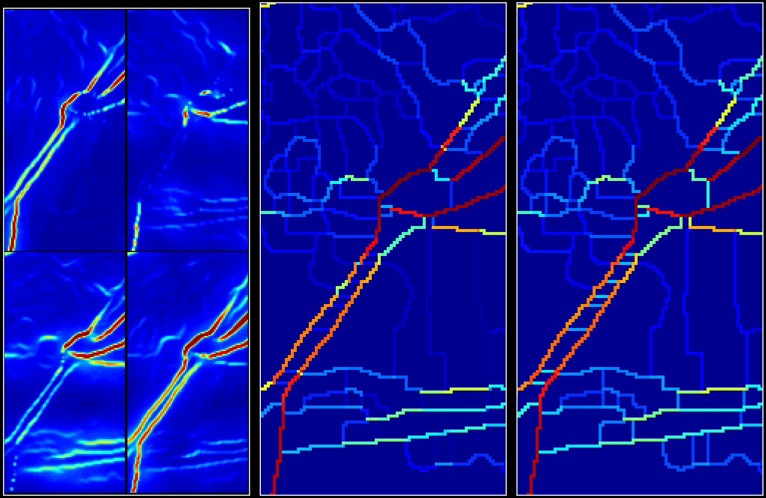

$pb(x, y, \theta)$ OWT Watershed

# Ultrametric Contour Map (UCM)

- Duality between closed, non-self-intersecting weighted contours and a hierarchy of regions[1]

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- Iteratively merge regions by removing minimum weight boundary
- Produces region tree
  - Root is entire image
  - Leaves are $\mathcal{P}_0$
  - $Height(R)$ is boundary threshold at which $R$ first appears
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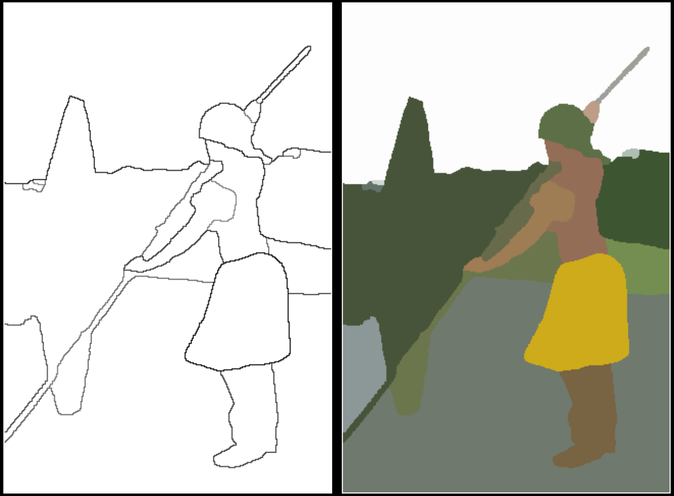
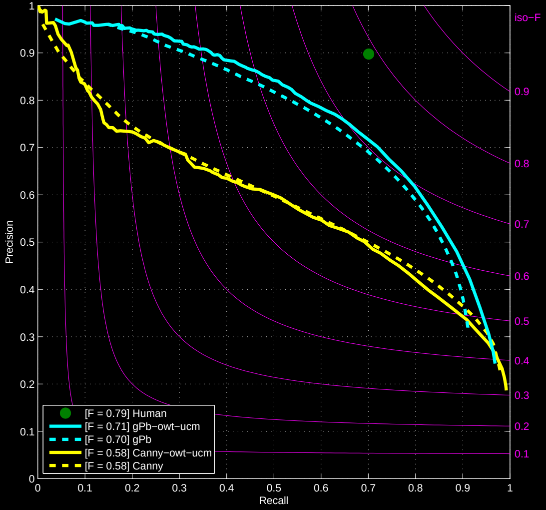
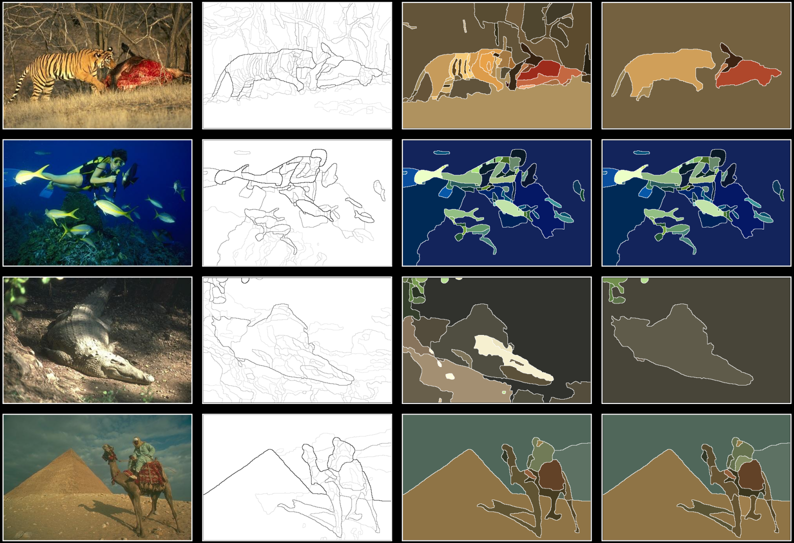


# OWT-UCM Preserves Boundary Quality



# Hierarchical Segmentation Results



*gPb*-owt-ucm ODS OIS

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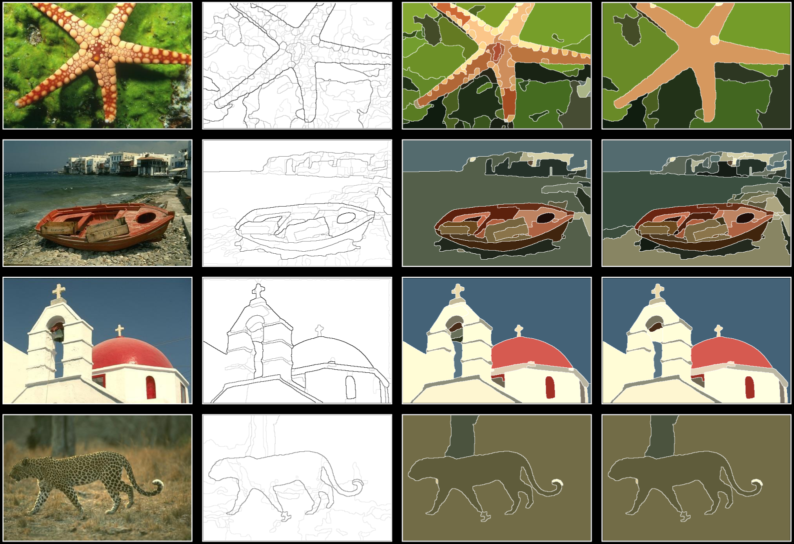
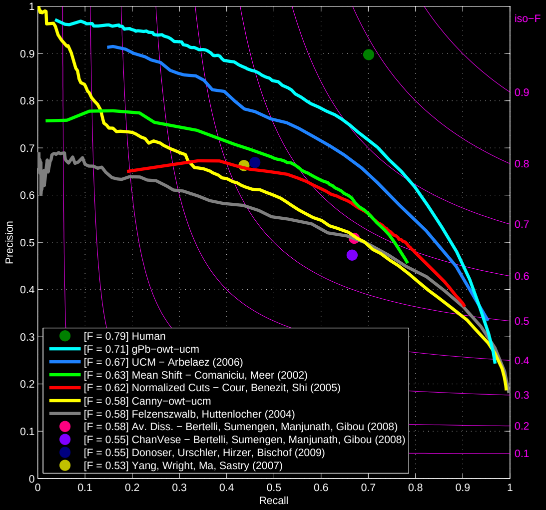


*gPb*-owt-ucm ODS OIS

# Empirical Evaluation

# Benchmarking Region Boundaries



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# Variation of Information

Distance between two clusterings of data $C$ and $C'$ given by

$$VI(C, C') = H(C) + H(C') - 2I(C, C')$$

Here $C$ and $C'$ are test and ground-truth segmentations.

# Probabilistic Rand Index

Given a set of ground-truth segmentations $\{G_k\}$,

$$PRI(S, \{G_k\}) = \frac{1}{T} \sum_{i<j} [c_{ij} p_{ij} + (1 - c_{ij})(1 - p_{ij})]$$

where $c_{ij}$ is the event that pixels $i$ and $j$ have the same label and $p_{ij}$ its probability.

# Segment Covering

Overlap between two regions $R$ and $R'$:

$$\mathcal{O}(R, R') = \frac{|R \cap R'|}{|R \cup R'|}$$

Covering of a segmentation $S$ by a segmentation $S'$:

$$\mathcal{C}(S' \to S) = \frac{1}{N} \sum_{R \in S} |R| \cdot \max_{R' \in S'} \mathcal{O}(R, R')$$

We report the covering of groundtruth by test.

# Region Benchmarks on the BSDS

| | Covering | | | PRI | | VI | |
|---|---|---|---|---|---|---|---|
| | ODS | OIS | Best | ODS | OIS | ODS | OIS |
| Human | 0.73 | 0.73 | – | 0.87 | 0.87 | 1.16 | 1.16 |
| gPb-owt-ucm | **0.59** | **0.65** | **0.75** | **0.81** | **0.85** | **1.65** | **1.47** |
| Mean Shift | 0.54 | 0.58 | 0.66 | 0.78 | 0.80 | 1.83 | 1.63 |
| Felz-Hutt | 0.51 | 0.58 | 0.68 | 0.77 | 0.82 | 2.15 | 1.79 |
| Canny-owt-ucm | 0.48 | 0.56 | 0.66 | 0.77 | 0.82 | 2.11 | 1.81 |
| NCuts | 0.44 | 0.53 | 0.66 | 0.75 | 0.79 | 2.18 | 1.84 |
| Total Var. | 0.57 | – | – | 0.78 | – | 1.81 | – |
| T+B Encode | 0.54 | – | – | 0.78 | – | 1.86 | – |
| Av. Diss. | 0.47 | – | – | 0.76 | – | 2.62 | – |
| ChanVese | 0.49 | – | – | 0.75 | – | 2.54 | – |

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  - User marks foreground/background
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- Alternative: use precomputed segmentation tree[4]
  - $Distance(R_1, R_2) = min\{Height(R) : R_1, R_2 \subseteq R\}$
  - Assign missing labels using closest labeled region

[4] P. Arbeláez and L. Cohen. "Constrained Image Segmentation from Hierarchical Boundaries", CVPR, 2008

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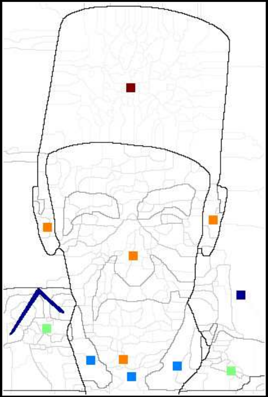
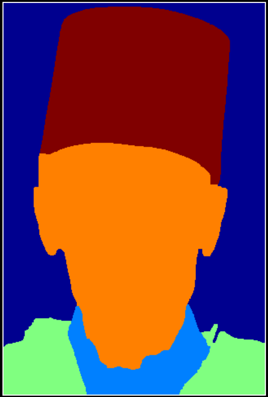
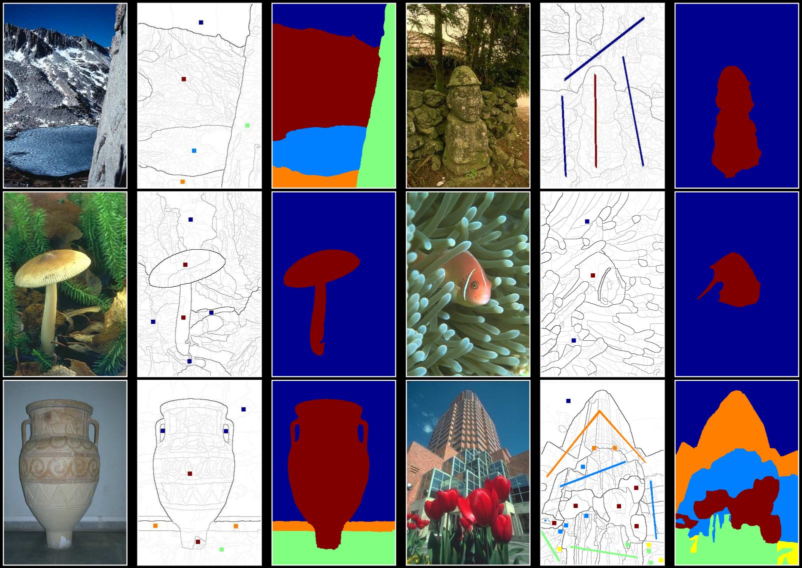


User Annotation



Automatic Refinement

# Interactive Segmentation



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- Detector input should be scale-dependent
- Generate scale-dependent contours/segments

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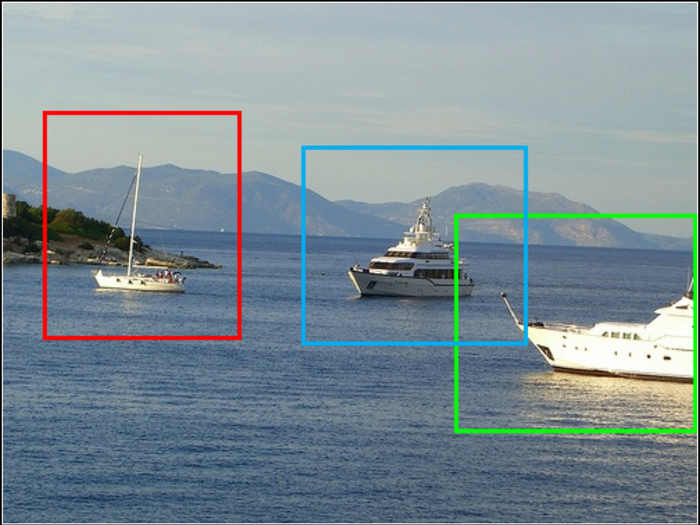

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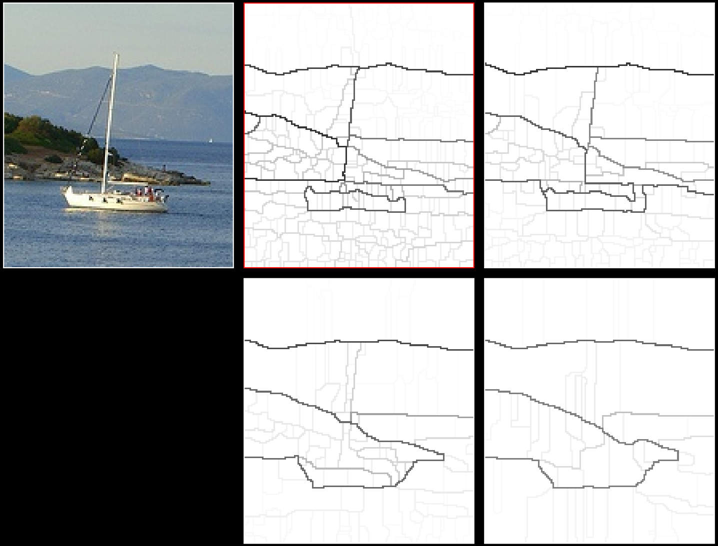

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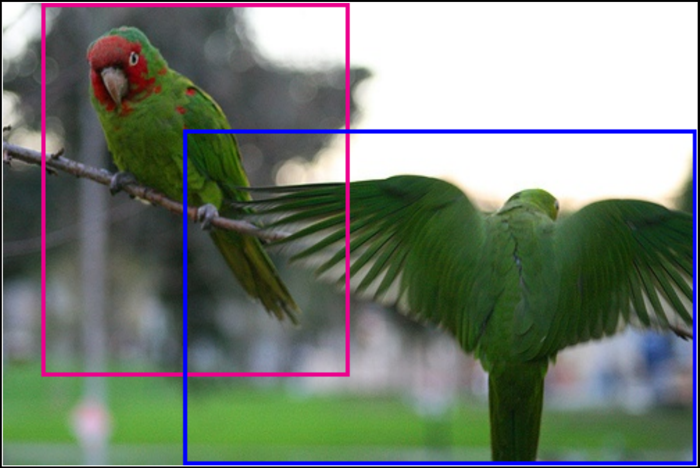

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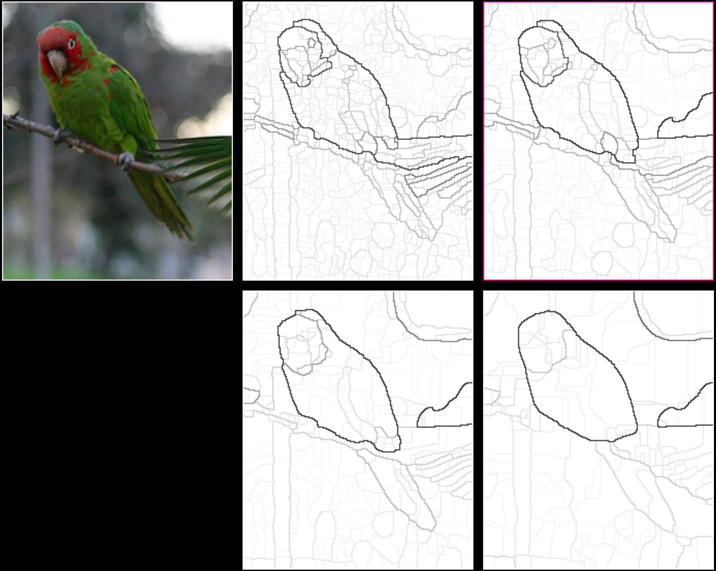

Thank You

# Take-Home Messages

- Image segmentation, at least in the BSDS setting, is a well-posed problem and the high consistency among human segmentations allows for its study on empirical bases.
- Canny is <u>not</u> as good as you get. The existence of a quantitative evaluation framework has led to measurable progress in the field over the last decade.
- Image segmentation and contour detection are two aspects of the same problem and can be studied jointly. Our particular approach consists in reducing the former to the latter.
- Berkeley Segmentation Resources:

  http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/resources.html