A Tour of Image Segmentation

Dr. Scott Cohen | Adobe Research

Image Segmentation

- Segment image pixels into different classes

- 2 Classes : Boy (Foreground), Not Boy (Background)

Demo: Adobe Photoshop Quick Select Tool

- Scott Cohen, Gregg Wilensky, Jeff Chien (Adobe)

Segmentation Variations

- How many classes?
- How are the classes defined?
- What features are used to compute the segmentation?
- Hard Segmentation or Soft Segmentation?
  - Hard: a pixel is assigned to exactly one class
  - Soft: a pixel may be assigned to more than one class
- Automatic or Interactive computation?
  - What user input is provided?
- How many images are segmented?

Interactive Binary Segmentation

- User Strokes (Scribbles) in Foreground and Background

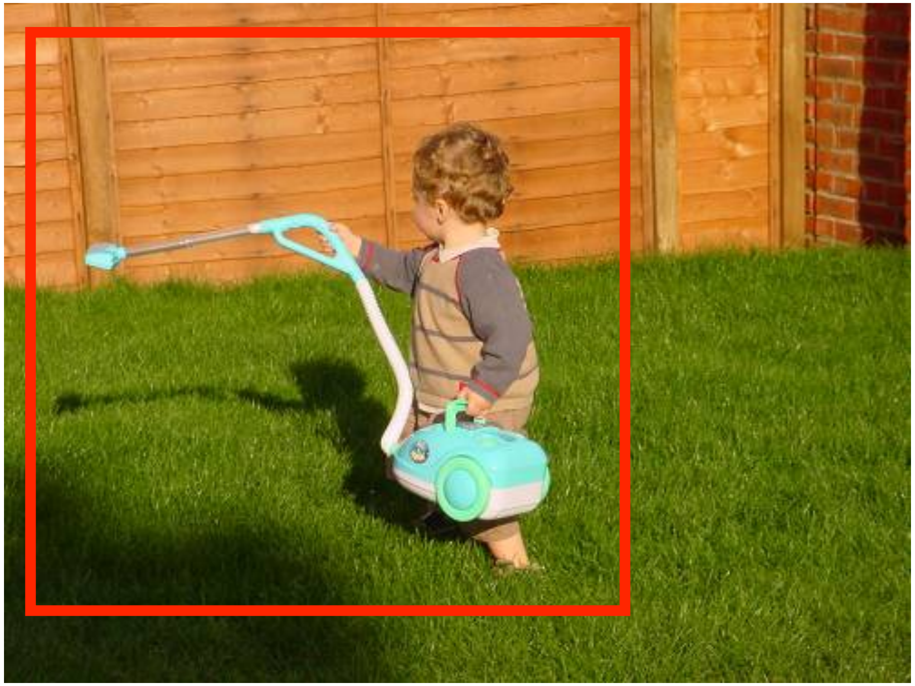
User Intent

Desired Segmentation

Interactive Graph Cuts for Optimal Boundary & Region Segmentation
Boykov,Jolly (ICCV 2001)

Interactive Binary Segmentation

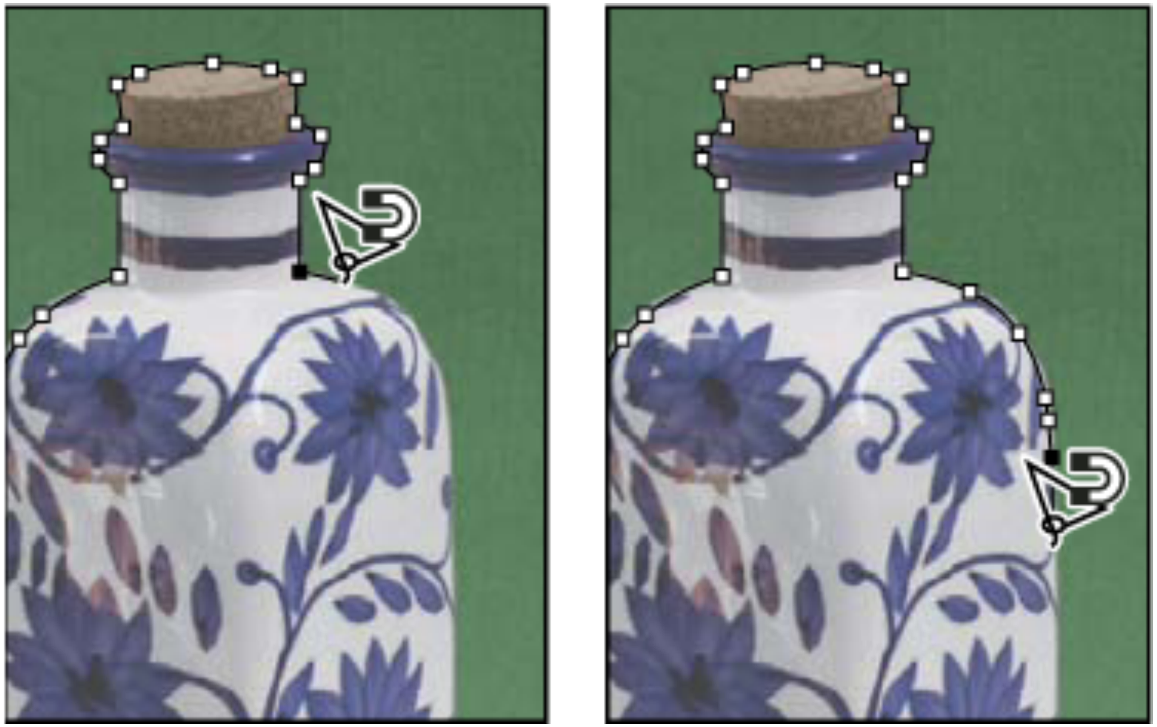
- GrabCut: Draw a rectangle around the object to select



GrabCut: Interactive Foreground Extraction using Iterated Graph Cuts
Rother, Kolmogorov, Blake (Siggraph 2004)

Interactive Binary Segmentation

- Magnetic Lasso: Trace around the object to select



Intelligent Scissors for Image Composition
Mortensen, Barrett (Siggraph 1995)

Automatic Binary Segmentation

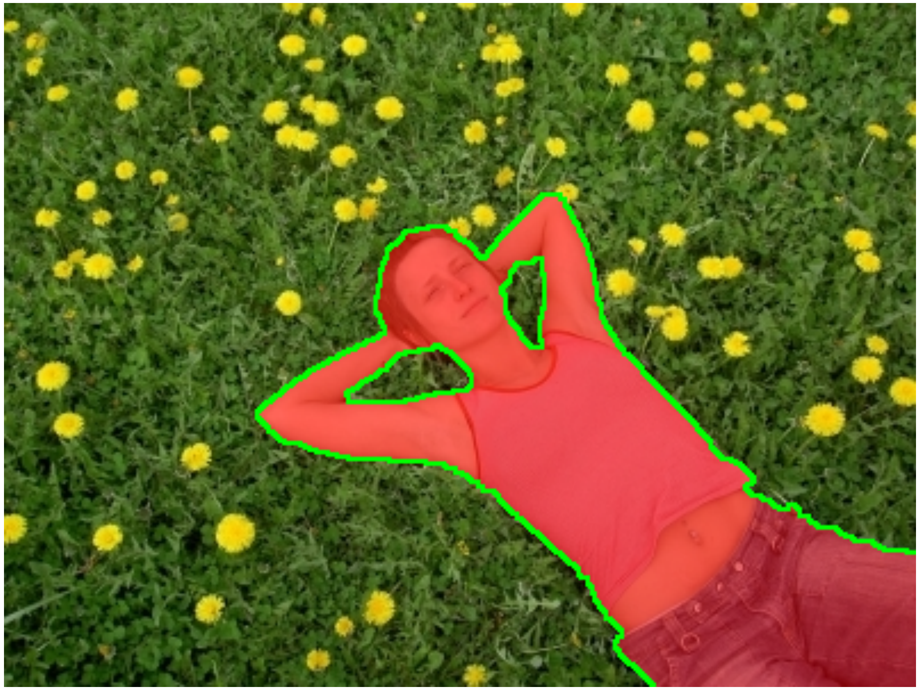
- Segment the "Salient" Region

Automatic Binary Segmentation

- Segment the “Salient” Region

Automatic Binary Segmentation

- Segment the "Salient" Region



Automatic Binary Segmentation

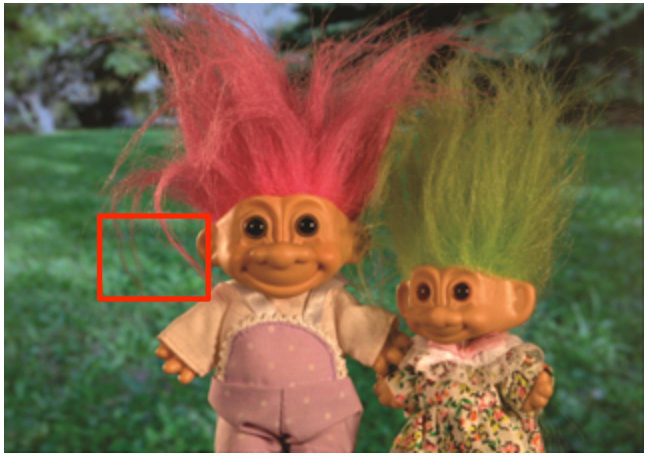
- Segment In-focus Regions

Input Image

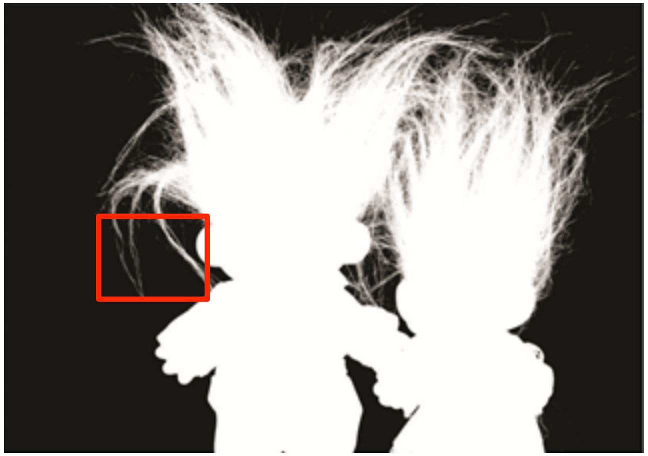
Output Segmentation

Image Matting

- Soft Binary Segmentation $I_p = \alpha_p F_p + (1-\alpha_p) B_p$



Input Image I



Output Segmentation $\alpha \in [0,1]$

Image Matting : Compositing Application

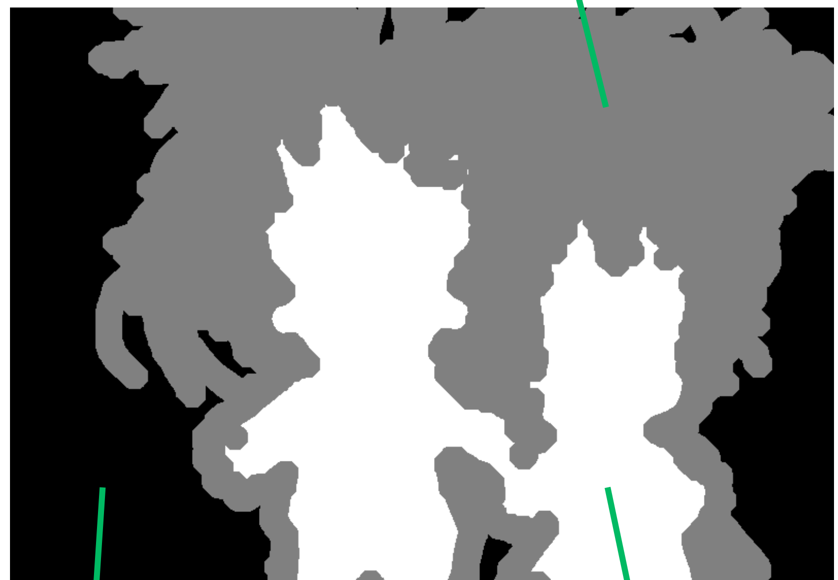
$$I_p = \alpha_p F_p + (1 - \alpha_p) B_p$$

$$\hat{I}_p = \alpha_p^{01} F_p + (1 - \alpha_p^{01}) \hat{B}_p$$

Image Matting : Trimap Input

$$I_p = \alpha_p F_p + (1 - \alpha_p) B_p$$

Unknown Region



Known Background

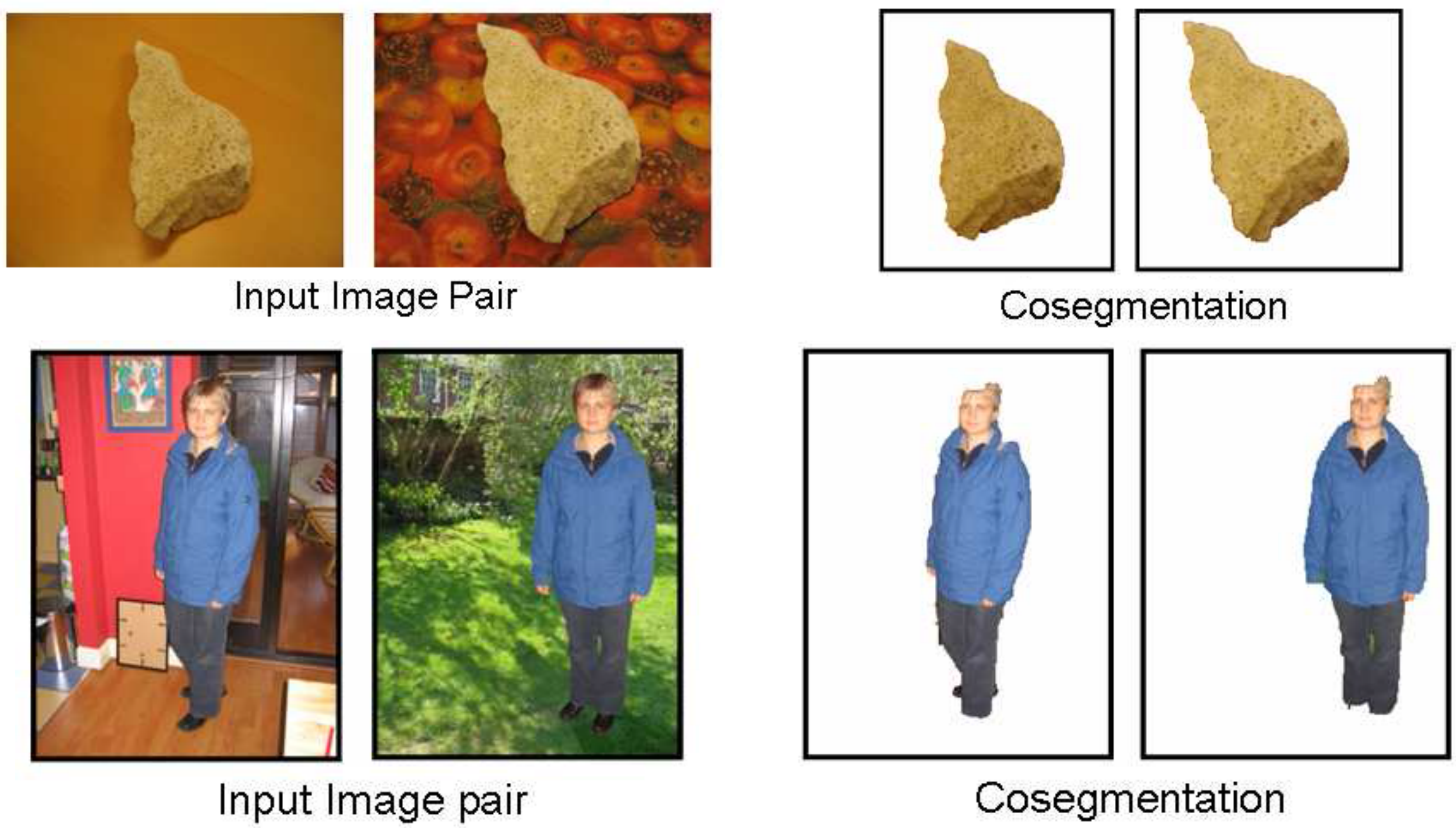
Known Foreground

Demo: Interactive Matting

- Brian Price, Scott Cohen (Adobe)

Co-Segmentation

- Segment the object in common in multiple images



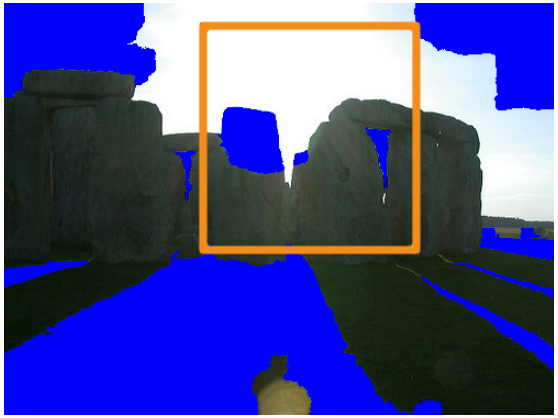
Cosegmentation of Image Pairs by Histogram Matching
Rother, Kolmogorov, Minka, Blake (CVPR 2006)

Co-Segmentation Methods

Method	Foregrounds	Backgrounds	Automatic or Interactive?	# of Images
Histogram Matching (CVPR06)	Same	Different	Automatic	2

Co-Segmentation : Similar BGs, Interactive, Many Images

iCoseg: Interactive Co-segmentation with Intelligent Scribble Guidance
Batra, Kowdle, Parikh, Luo, Chen (CVPR 2010)

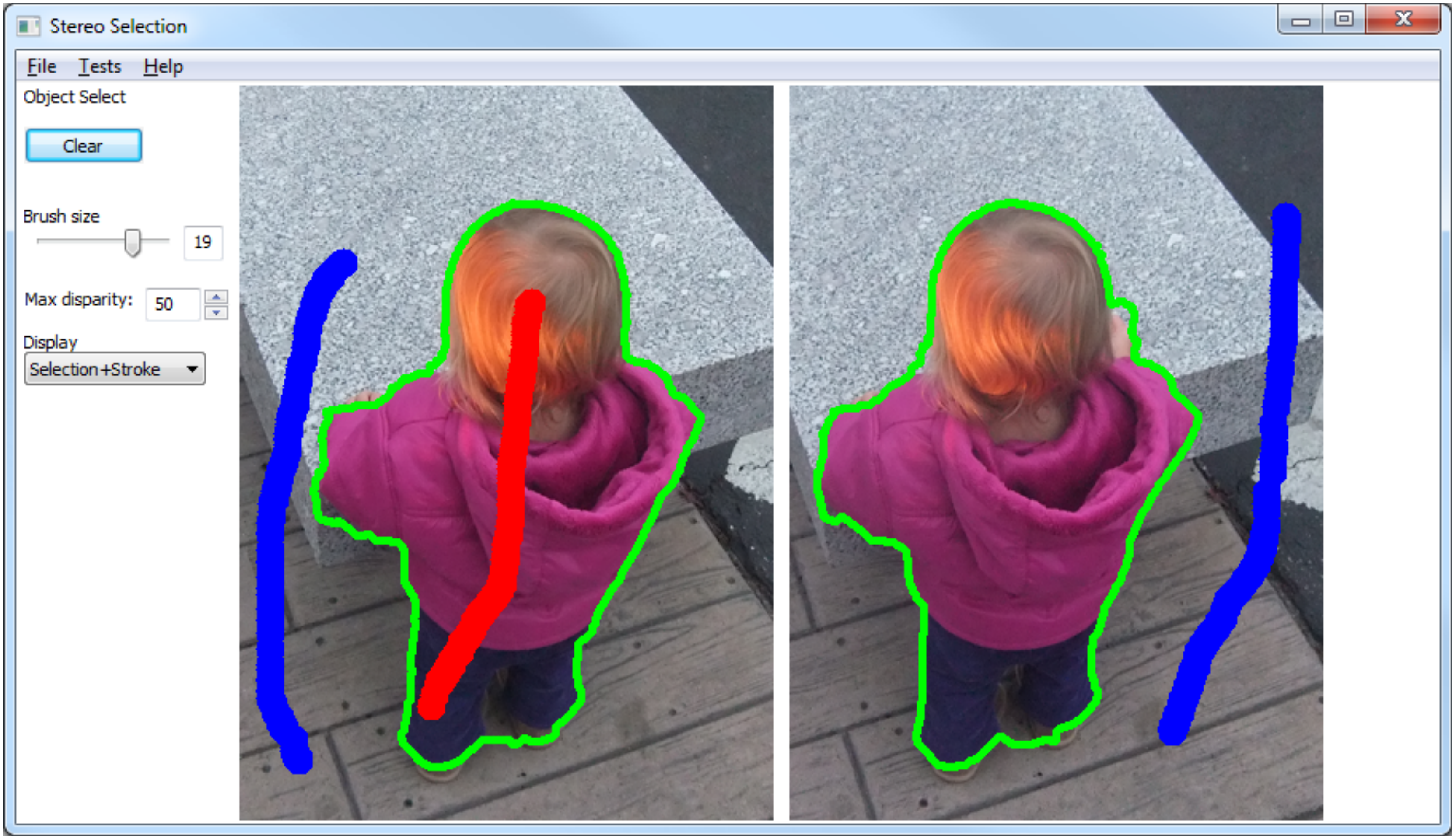


Co-Segmentation Methods

Method	Foregrounds	Backgrounds	Automatic or Interactive?	# of Images
Histogram Matching (CVPR06)	Same	Different	Automatic	2
iCoseg (CVPR10)	Similar	Similar	Interactive	Many

Stereo Co-Segmentation : Same BGs, Interactive, 2 Images

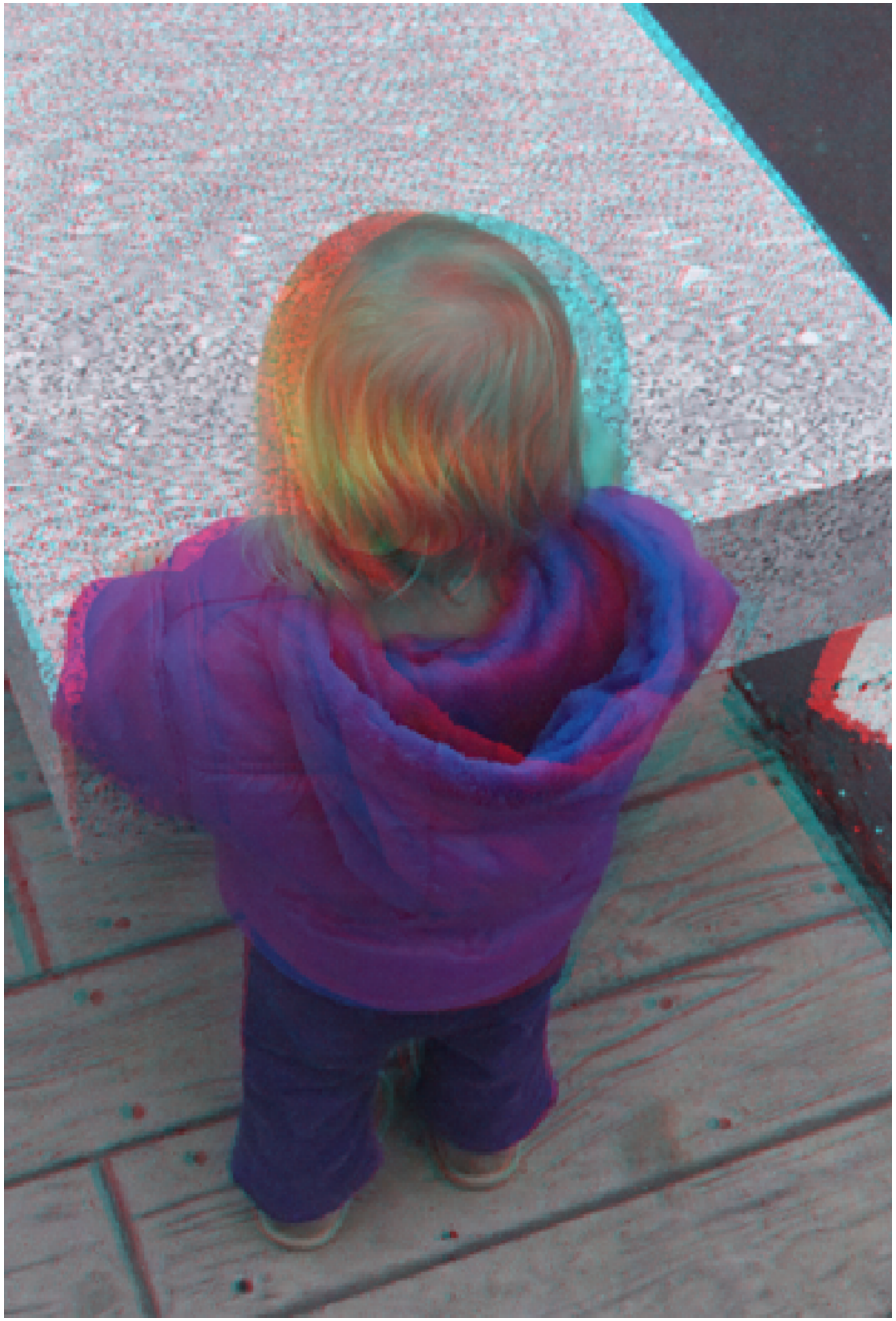
StereoCut: Consistent Interactive Object Selection in Stereo Image Pairs
Price, Cohen (ICCV 2011)

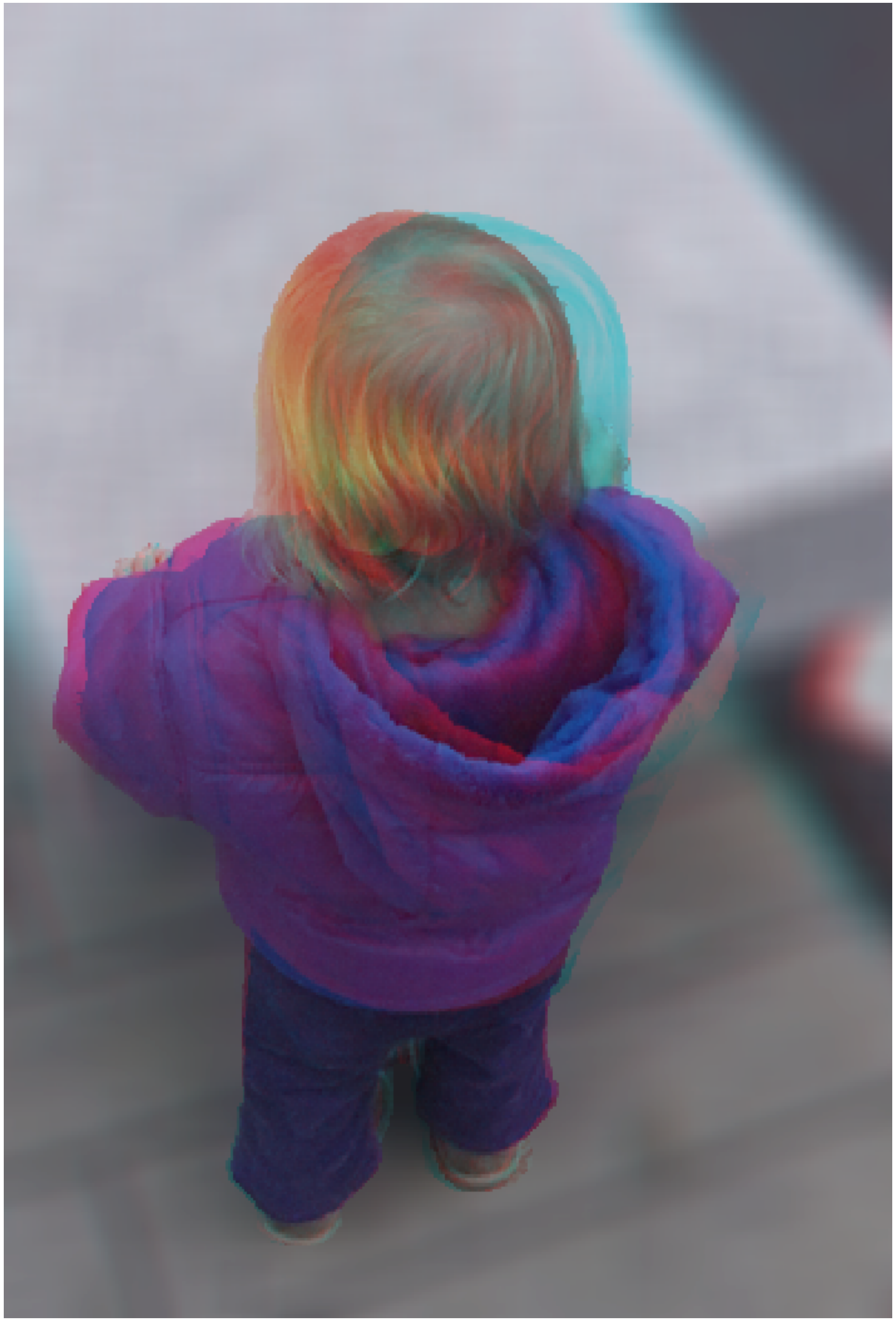


Stereo Co-Segmentation Applications

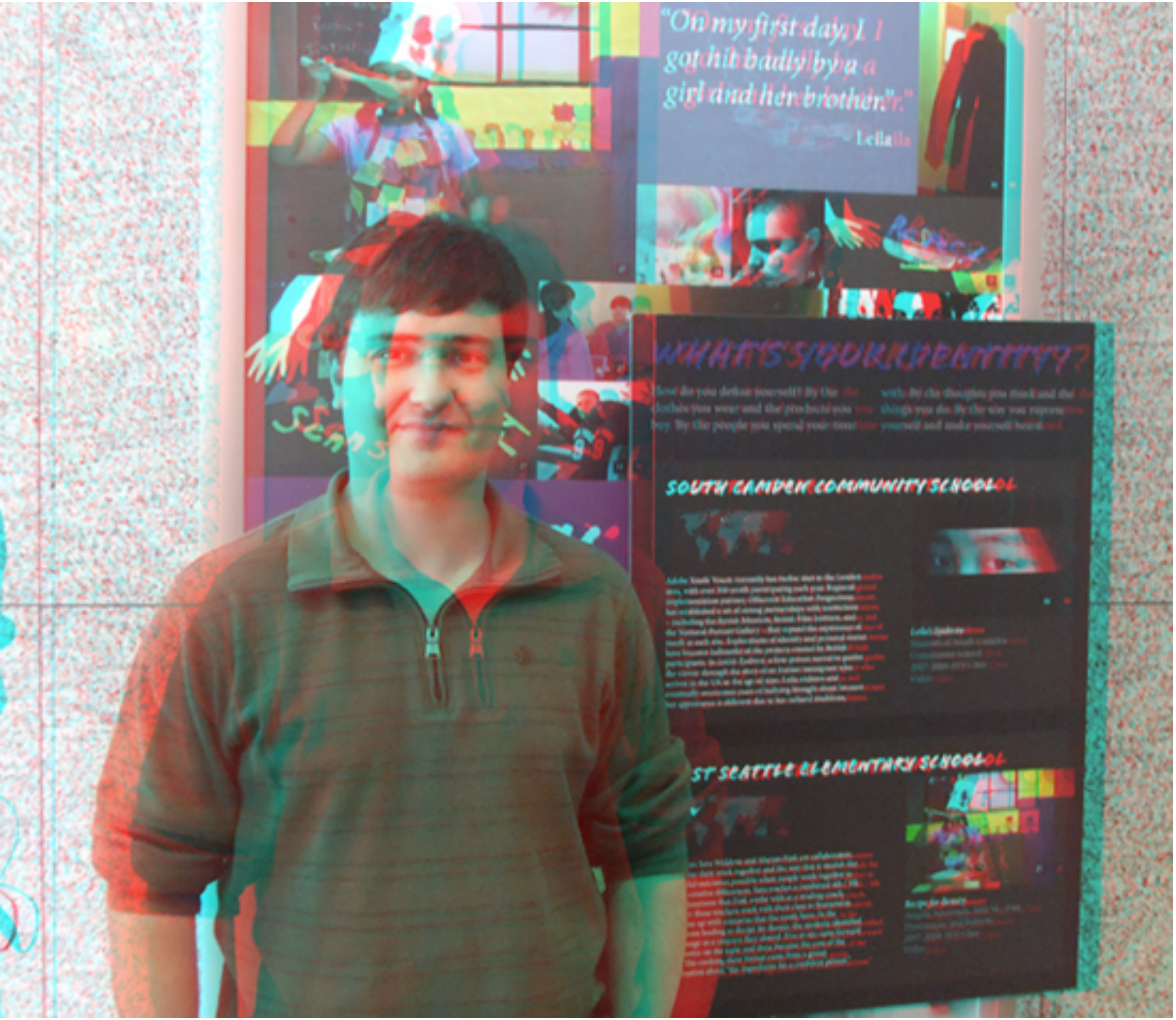
- Localized Stereo Editing
- Stereo Inpainting: remove Co-Segmented object from the stereo picture

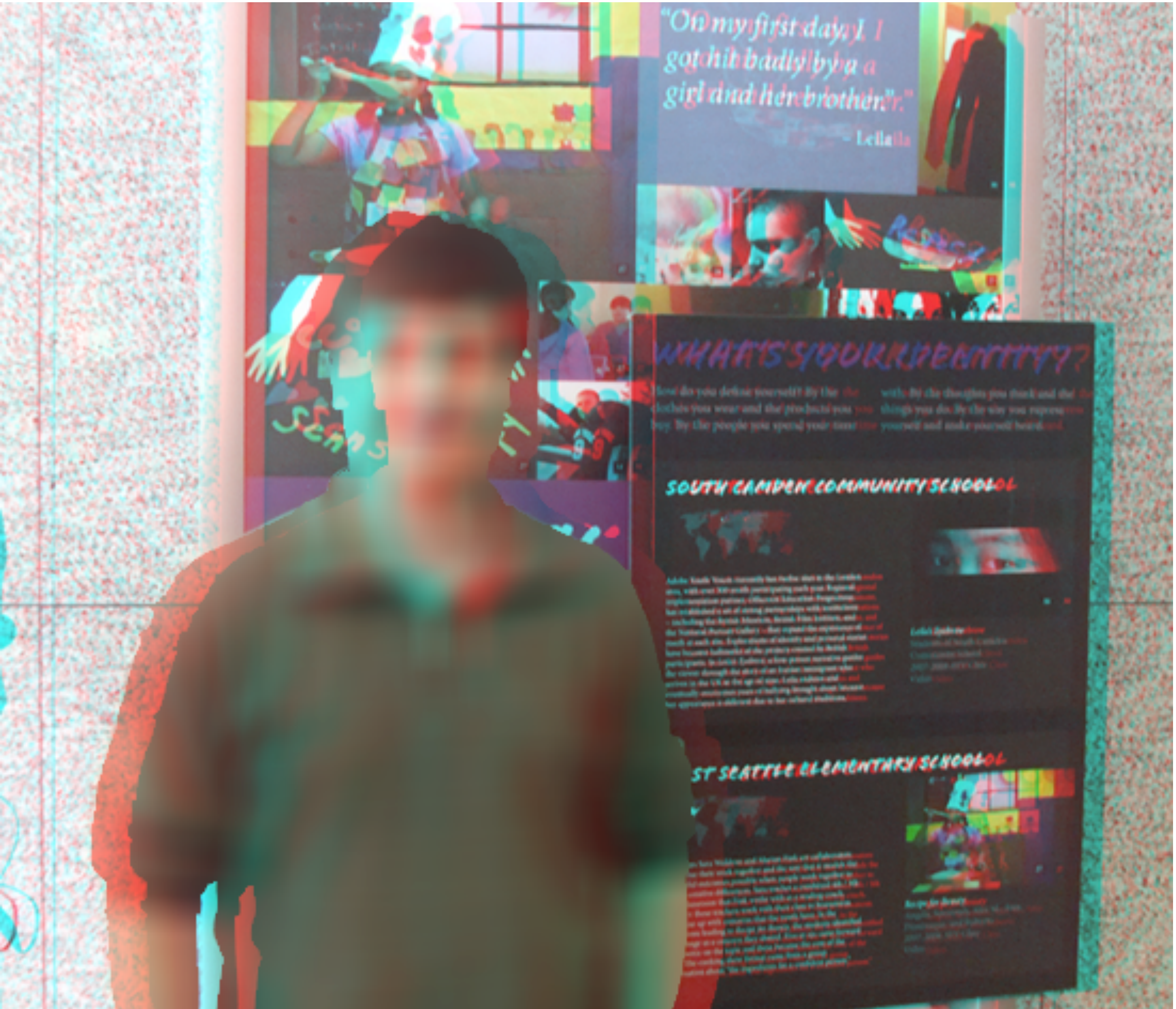
PatchMatch-based Content Completion of Stereo Image Pairs
Morse, Howard, Cohen, Price (3DimPVT 2012)






NAVY
2010


"On my first day, I got hit badly by a girl and her brother."
- Leila
WHAT'S YOUR IDENTITY?
SOUTH CAMDEN COMMUNITY SCHOOL
ST SEATTLE ELEMENTARY SCHOOL


"On my first day, I got hit badly by a girl and her brother."
– Leila
WHAT'S YOUR IDENTITY?
SOUTH CAMDEN COMMUNITY SCHOOL

Co-Segmentation Methods

Method	Foregrounds	Backgrounds	Automatic or Interactive?	# of Images
Histogram Matching (CVPR06)	Same	Different	Automatic	2
iCoseg (CVPR10)	Similar	Similar	Interactive	Many
Stereo (ICCV11)	Same	Same	Interactive	2

Co-Segmentation : Similar BGs, Automatic, Many Images

Unsupervised Joint Object Discovery and Segmentation in Internet Images
Rubinstein, Joulin, Kopf, Liu (CVPR 2013)

“Car” Internet Search

Input

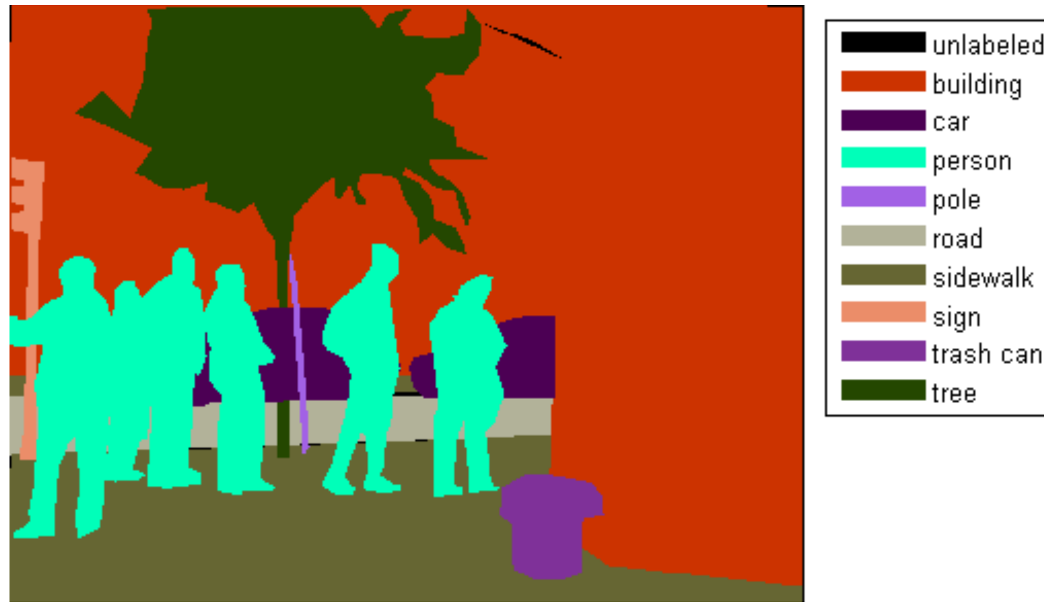
Output

Co-Segmentation Methods

Method	Foregrounds	Backgrounds	Automatic or Interactive?	# of Images
Histogram Matching (CVPR06)	Same	Different	Automatic	2
iCoseg (CVPR10)	Similar	Similar	Interactive	Many
Stereo (ICCV11)	Same	Same	Interactive	2
Object Discovery (CVPR13)	Similar, but more variation than iCoseg	Similar and Different	Automatic	Many

- Label each pixel in an image with its semantic category

Input Image



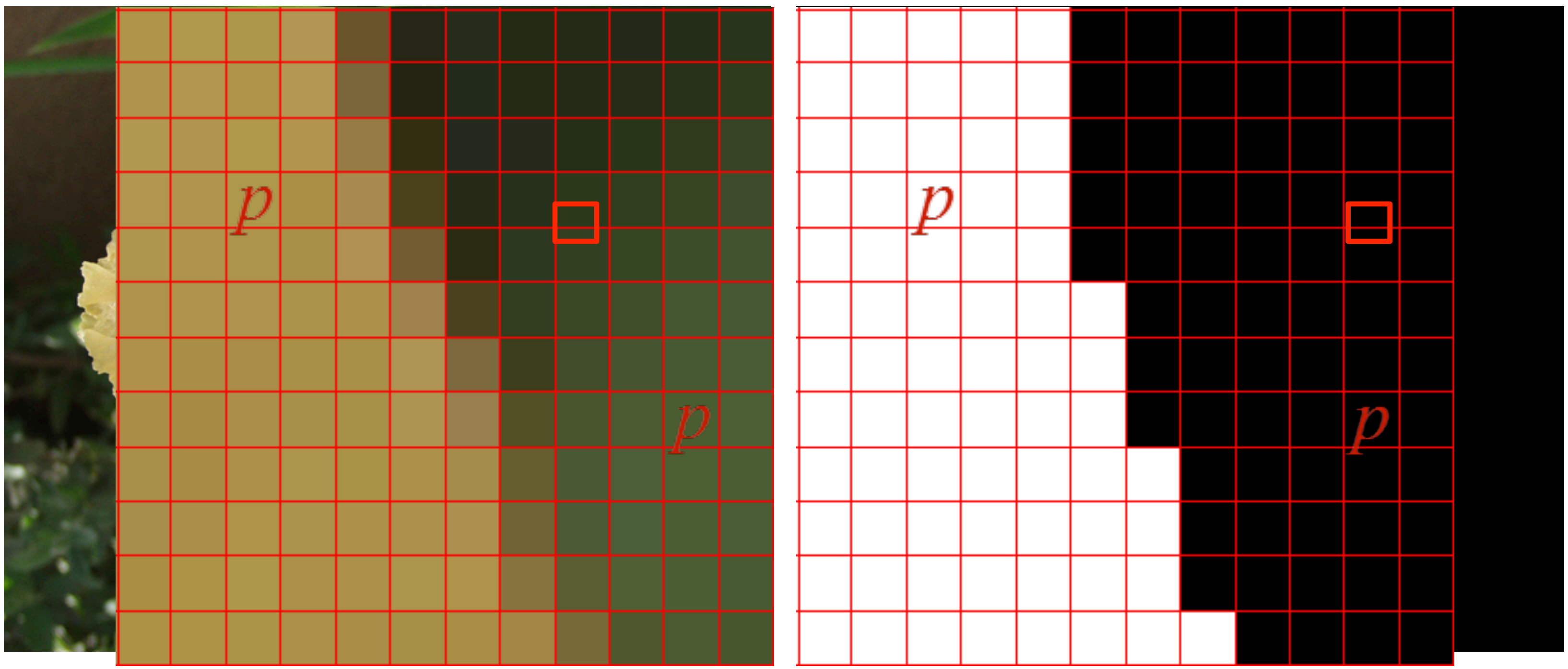
Desired Output

Adobe

Details About Some Segmentation Methods

- Common Framework
- Notation: Segmentation $X = \{x_p\}$

$I = \{I_p\}$ $\quad x_p = 1 \quad X = \{x_p\} \quad x_p = 0$

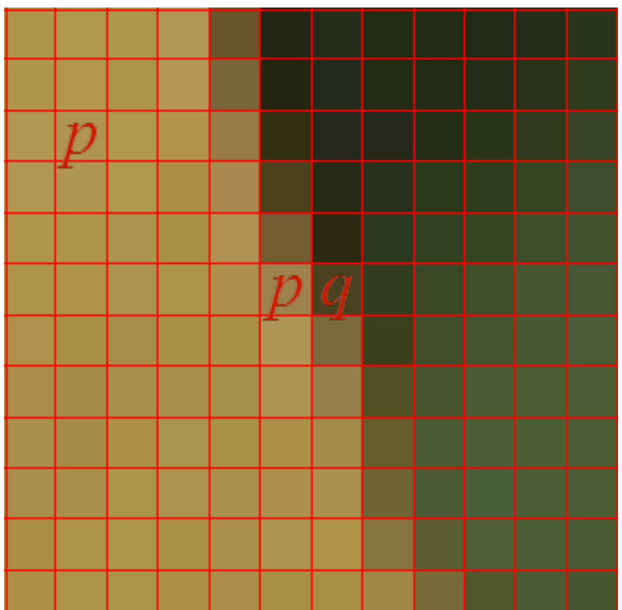


Common Energy Minimization Framework

- Energy function to measure quality of segmentation $X = \{x_p\}$

$$E(X) = \sum_p D_p(x_p) + \lambda \sum_{p,q \in N} V_{pq}(x_p, x_q)$$

* Global minimum found by min graphcut / maxflow algorithms



Data Term

$D_p(0) = \text{cost of labeling pixel p as BG}$
$D_p(1) = \text{cost of labeling pixel p as FG}$

Smoothness Term

$V_{pq}(1,0) = \text{cost of p as FG, q as BG}$
$V_{pq}(0,1) = \text{cost of p as BG, q as FG}$
$V_{pq}(0,0) = \text{cost of p as BG, q as BG} = 0$
$V_{pq}(1,1) = \text{cost of p as FG, q as FG} = 0$

Energy E for Stroke-based Binary Segmentation using Color

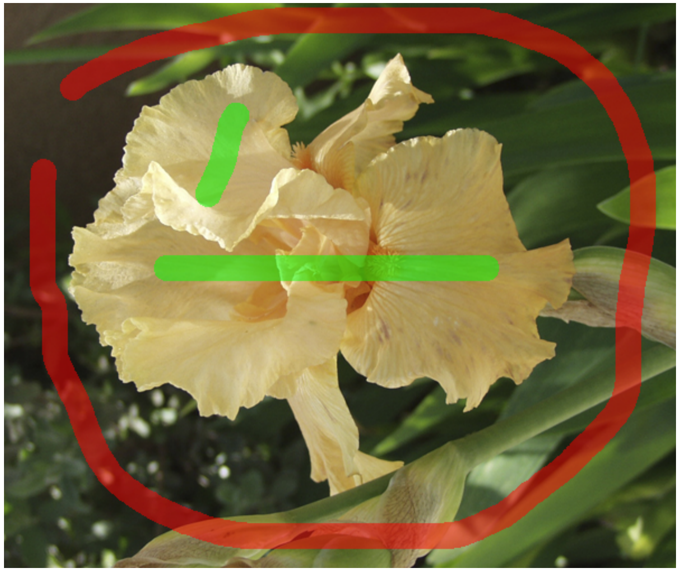
- K-means on FG Strokes

- K-means on BG Strokes

- ➔Probability $P_p(FG \mid I_p)$

$$
\begin{aligned}
D_p(FG) &= 0 \ \text{ if } \mathrm{p} \in \mathrm{F} \\
&= \infty \text{ if } \mathrm{p} \in \mathrm{B} \\
&= -\log \mathrm{P_p(FG \mid I_p)} \text{ otherwise}
\end{aligned}
$$

$$
\begin{aligned}
D_p(BG) &= 0 \ \text{ if } \mathrm{p} \in \mathrm{B} \\
&= \infty \text{ if } \mathrm{p} \in \mathrm{F} \\
&= -\log \mathrm{P_p(BG \mid I_p)} \text{ otherwise}
\end{aligned}
$$



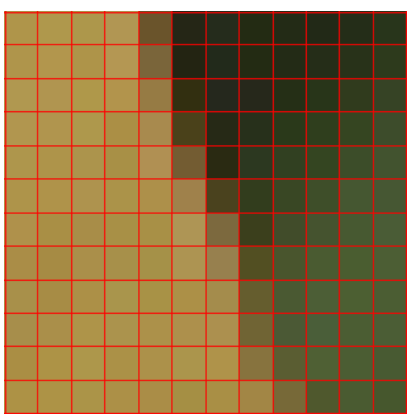
Energy E for Binary Segmentation: Smoothness

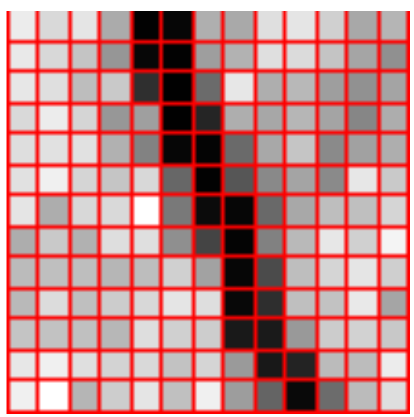
$$V_{pq}(BG, BG) = V_{pq}(FG, FG) = 0$$

- Encourage segmentation boundaries to occur at image edges

$$V_{pq}(FG, BG) = \exp\left(-\frac{\left\| I_p - I_q \right\|_2^2}{2\sigma^2} \right)$$

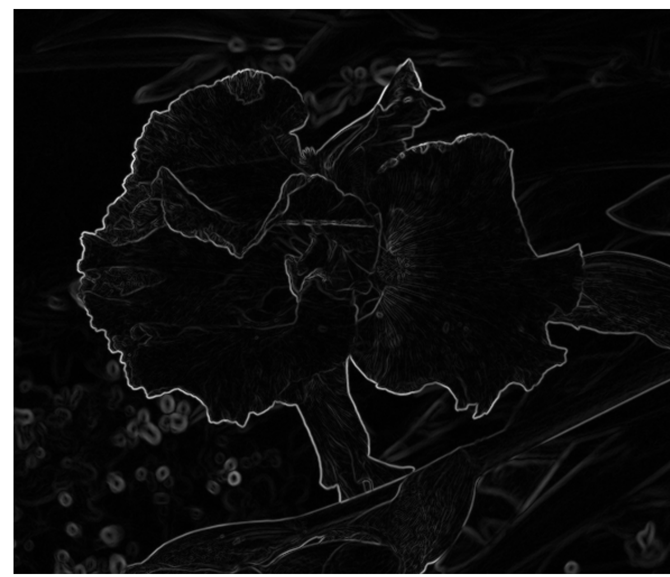
$$V_{pq}(BG, FG) = V_{pq}(FG, BG)$$





I

$\left\| \nabla I \right\|$

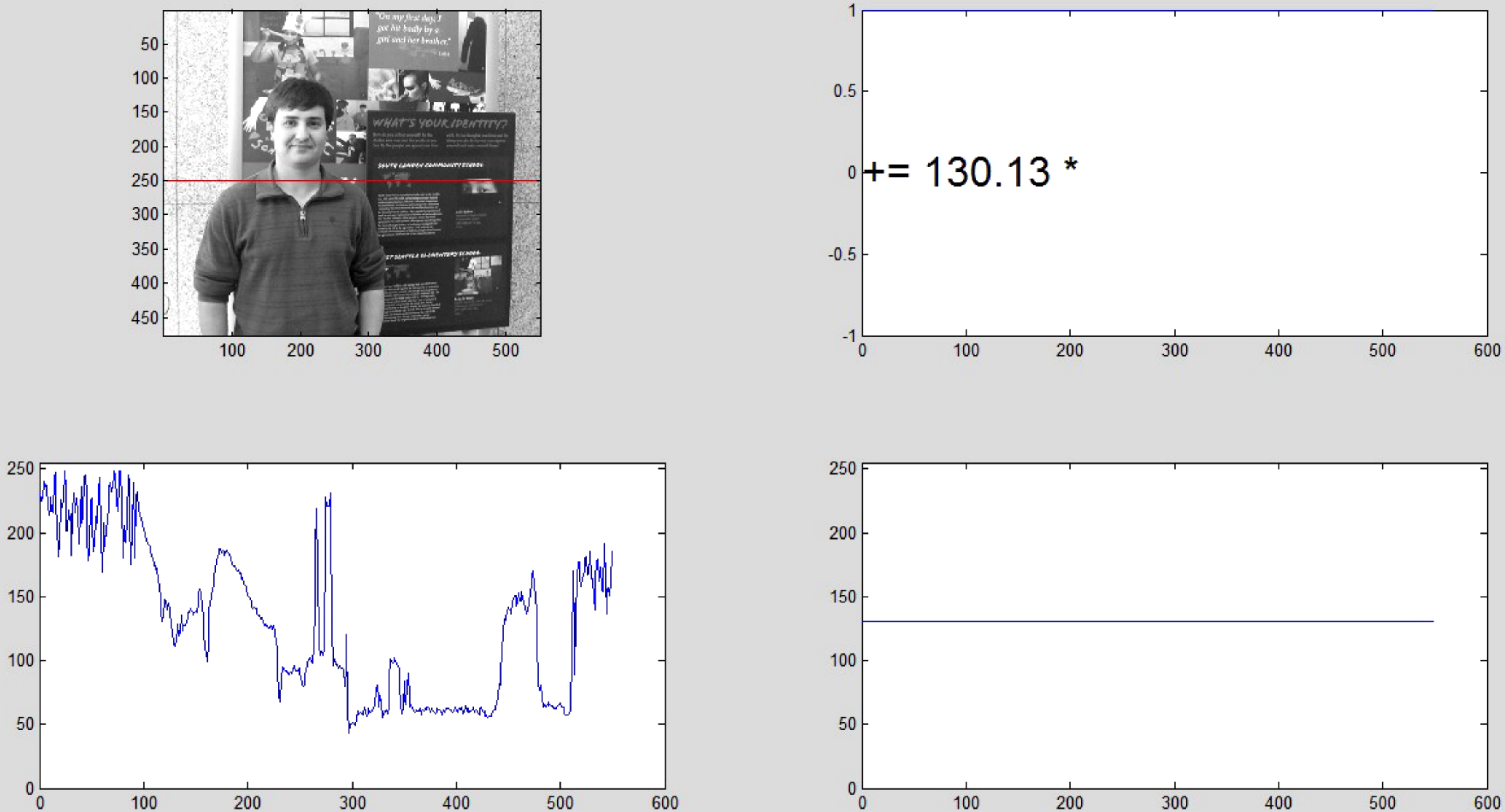


Why is V called the smoothness term?

$$E(X) = \sum_{p} D_p(x_p) + \lambda \sum_{p,q \in N} V_{pq}(x_p, x_q)$$

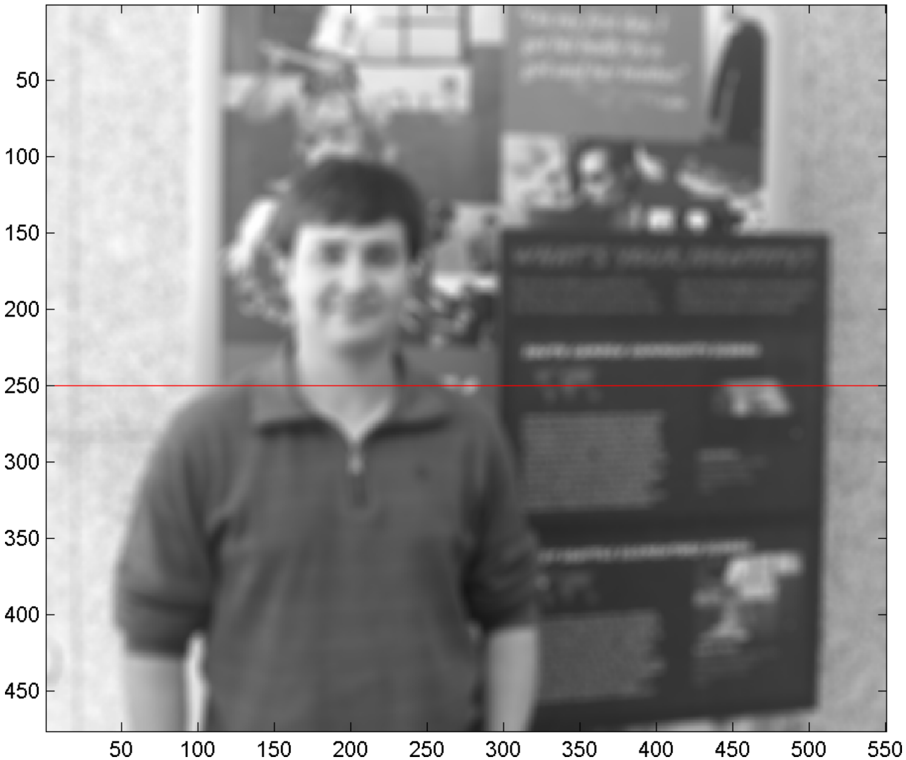
$$P_p(FG \mid I_p)$$

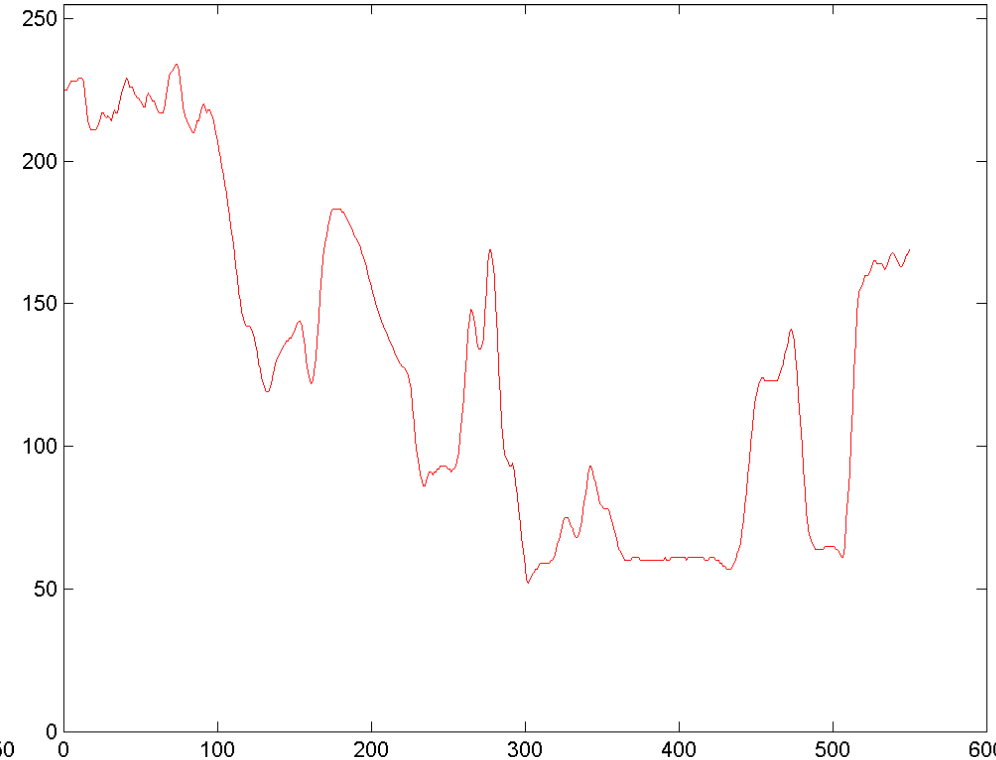
In-Focus Segmentation: Frequency Decomposition

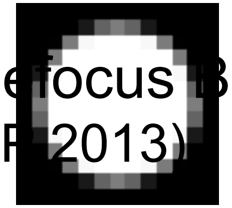


In-Focus Segmentation: Modeling Defocus Blur

- Larger blurs remove higher frequencies

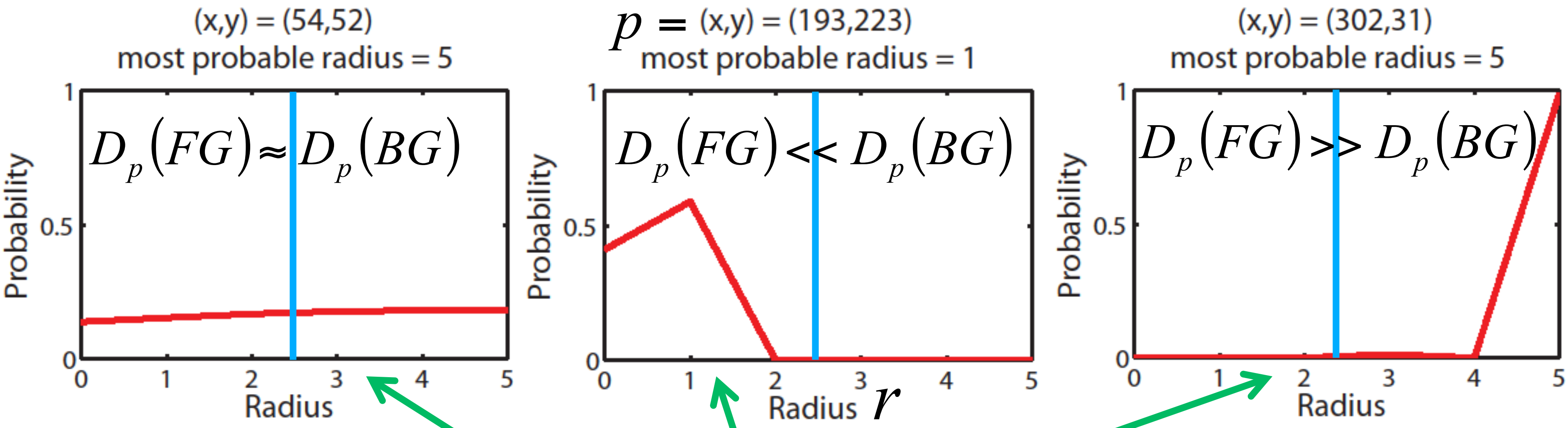




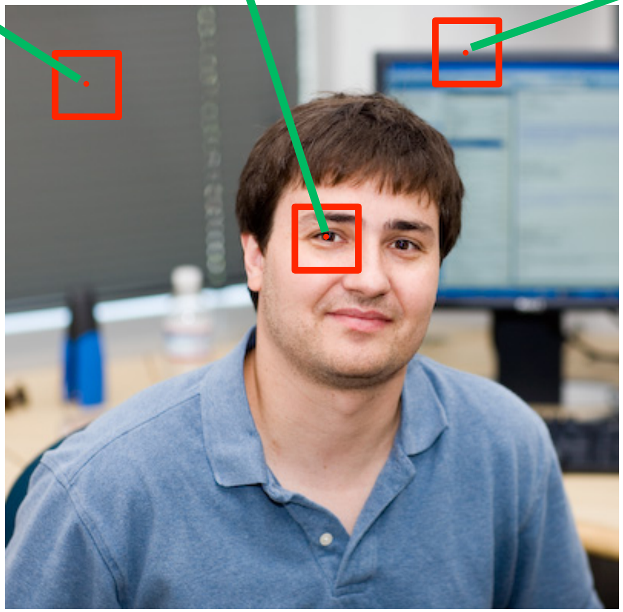


Estimating Spatially Varying Defocus Blur from A Single Image
Zhu, Cohen, Schiller, Milanfar (TIP 2013)

Out-of-Focus Blur Estimation



- Measure power across frequencies



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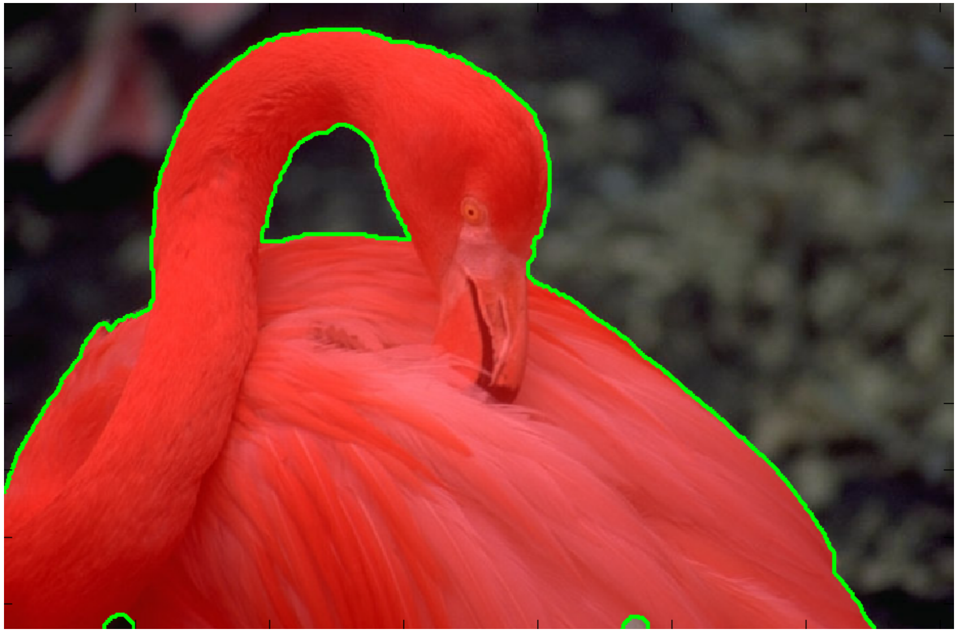
Automatic In-Focus Segmentation Results

$$E(X) = \sum_{p} D_p(x_p) + \lambda \sum_{p,q \in N} V_{pq}(x_p, x_q)$$

Automatic In-Focus Segmentation Results

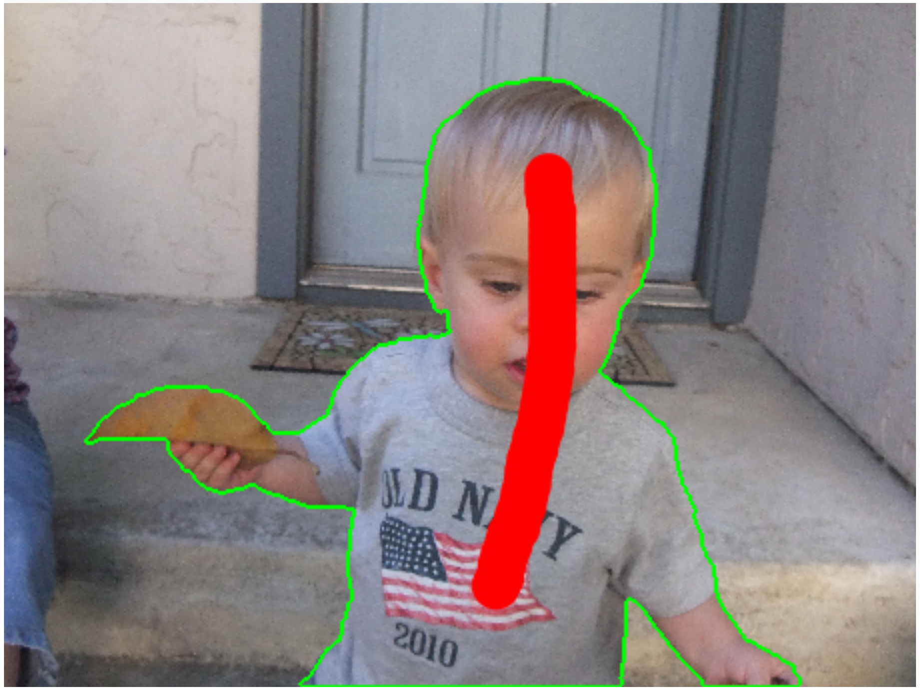


Automatic In-Focus Segmentation Results

- Works when foreground and background colors are similar

Automatic In-Focus Segmentation Results

Interactive Stereo Co-Segmentation

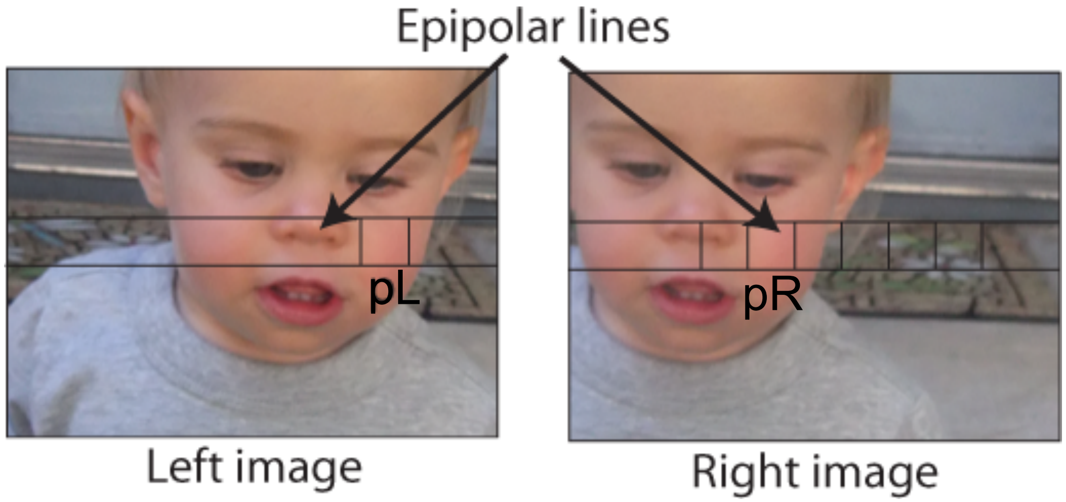


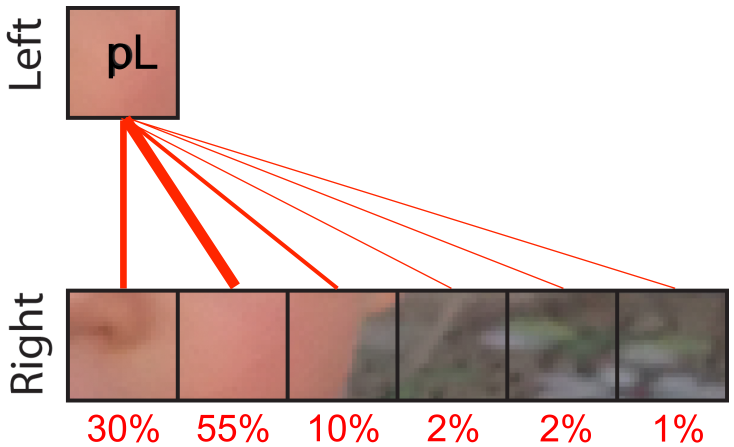
Left

Right

Energy E for Stereo Segmentation

- Add an energy term to include correspondence information

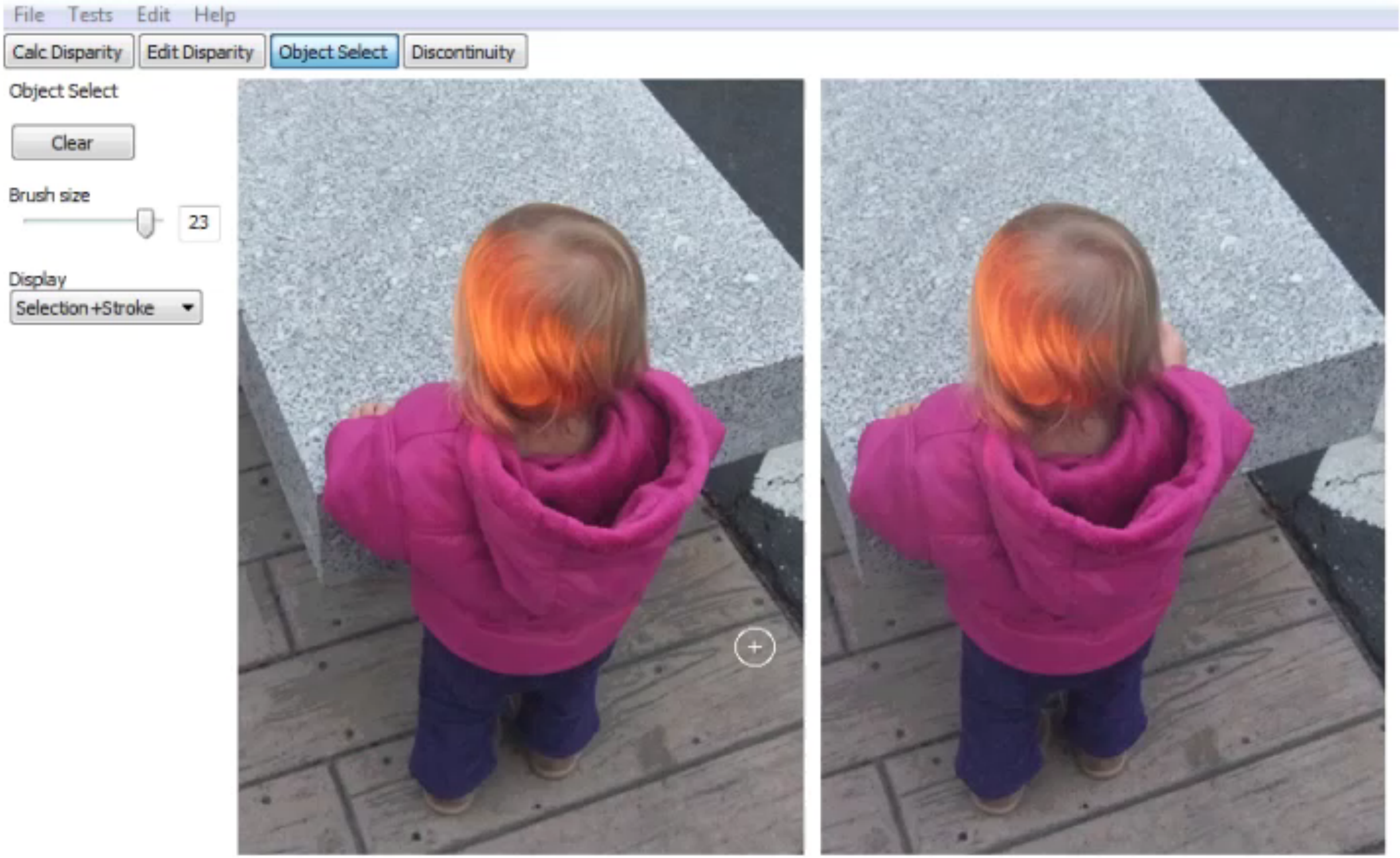




- If (pL,pR) likely correspond, then their labels should be same

$$E(X) = \sum_{p} D_p(x_p) + \lambda \sum_{p,q \in N} V_{pq}(x_p, x_q) \boxed{+ \mu \sum_{pL,pR} P_{match}(pL, pR) \left| x_{pL} - x_{pR} \right|}$$

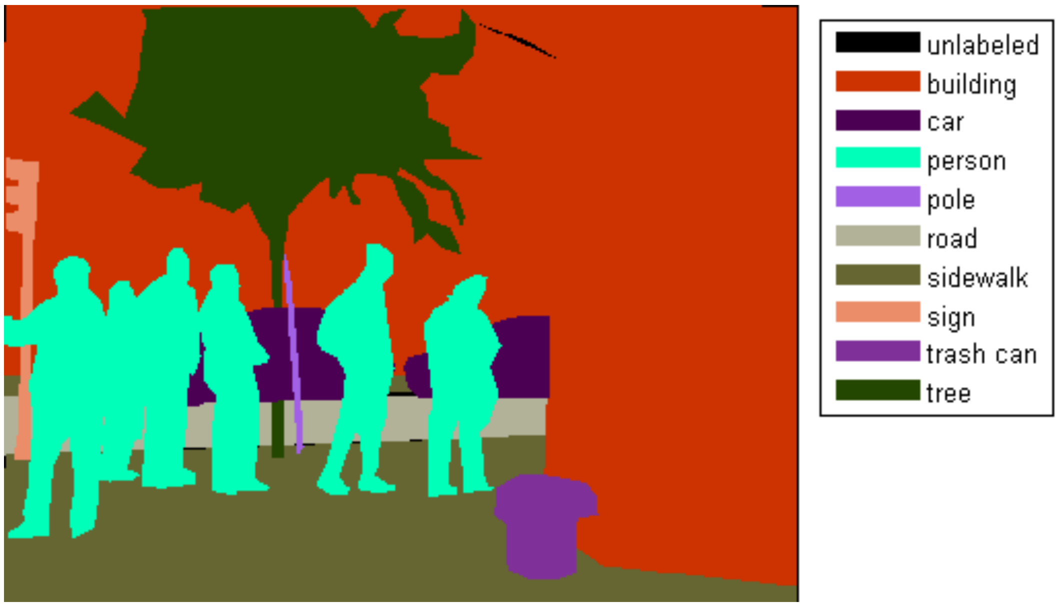
Stereo Segmentation Results



Scene Parsing | Semantic Segmentation

- Label each pixel in an image with its semantic category

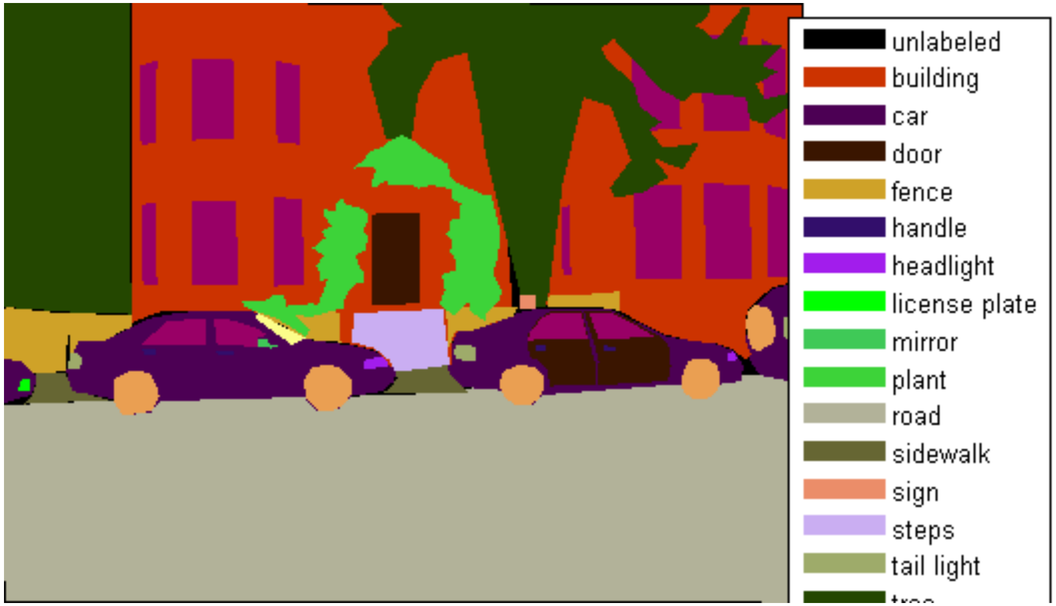
Input Image



Desired Output

Scene Parsing | Semantic Segmentation

- Training Data : Labeled Images (Input)
- SIFTflow : 2488 Labeled Training Images, 33 Classes
- LMSun : 45176 Labeled Training Images, 232 Classes

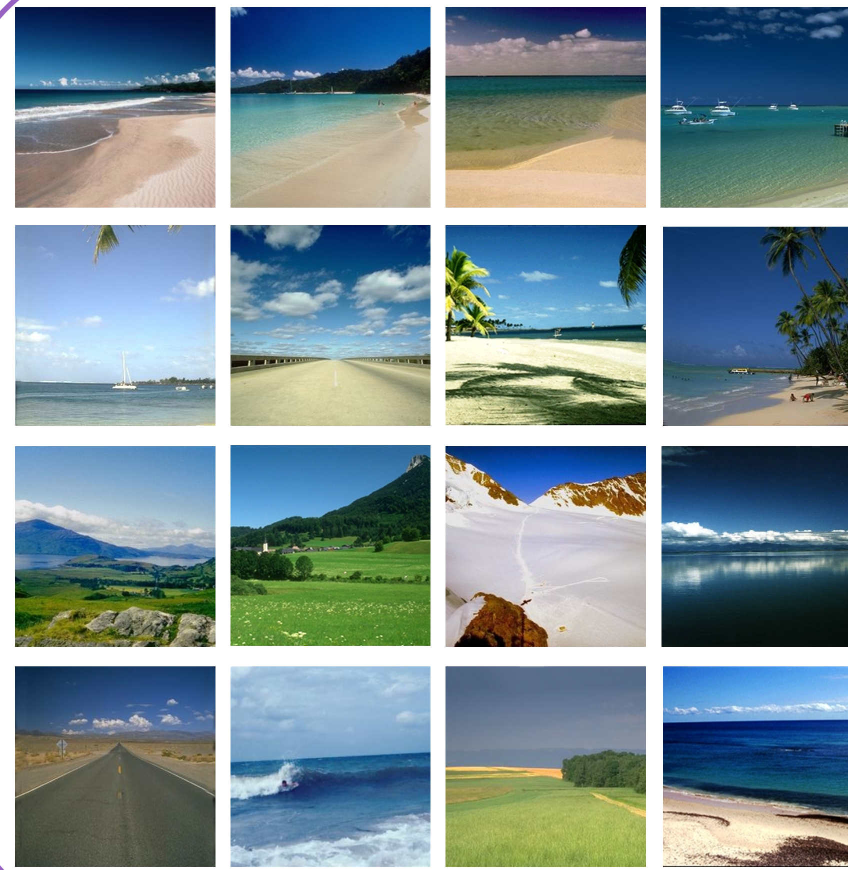


Scene Parsing | Semantic Segmentation

Input Image

Image Retrieval

Similar Training Images



Sea, sand, sky, mountain, field, tree, rock, plant, road, grass, boat, river, person

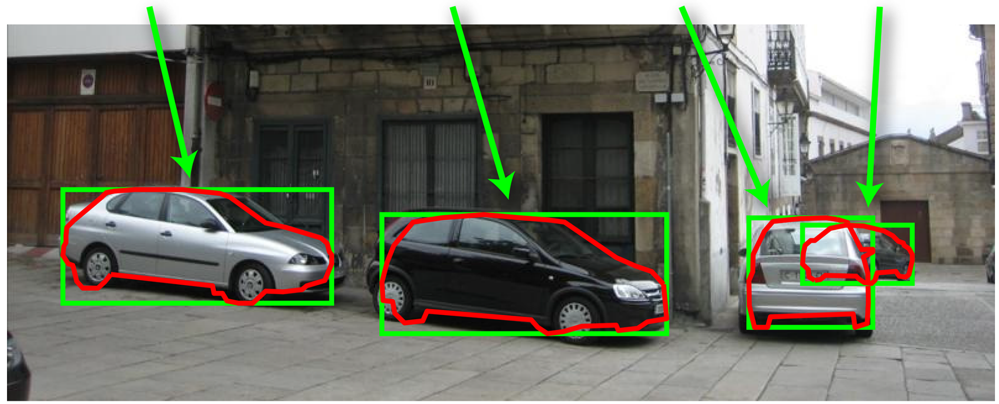
$$P_p(x_p = \text{sea}), P_p(x_p = \text{sand}), \ldots$$

Scene Parsing | Semantic Segmentation

- Tighe, Lazebnik. Finding things: Image parsing with regions and per-exemplar detectors. CVPR13

Cars from Similar Training Images

Test Image



Likelihood of Car

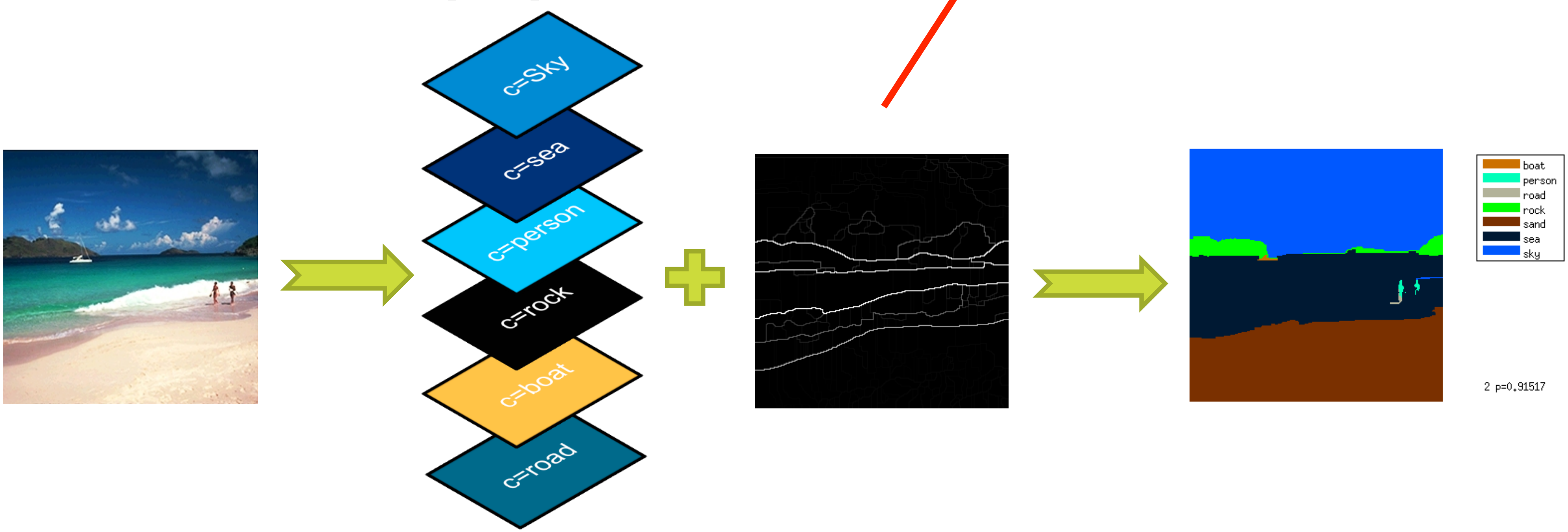
$$P_p(x_p = \text{car})$$

Energy E for Scene Parsing | Semantic Segmentation

$$E(X) = \sum_{p} D_p(x_p) + \lambda \sum_{p,q \in N} V_{pq}(x_p, x_q)$$

$$V_{pq}(\text{sea}, \text{sand})$$
$$V_{pq}(\text{sky}, \text{rock})$$
$$\vdots$$
$$V_{pq}(\text{sofa}, \text{sea})$$
$$\vdots$$

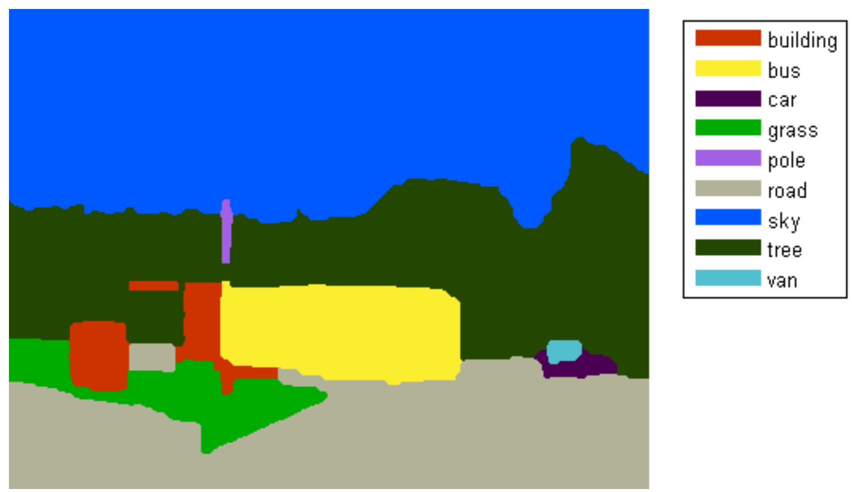
$$P_p(x_p = c)$$



Scene Parsing | Semantic Segmentation Results

Image

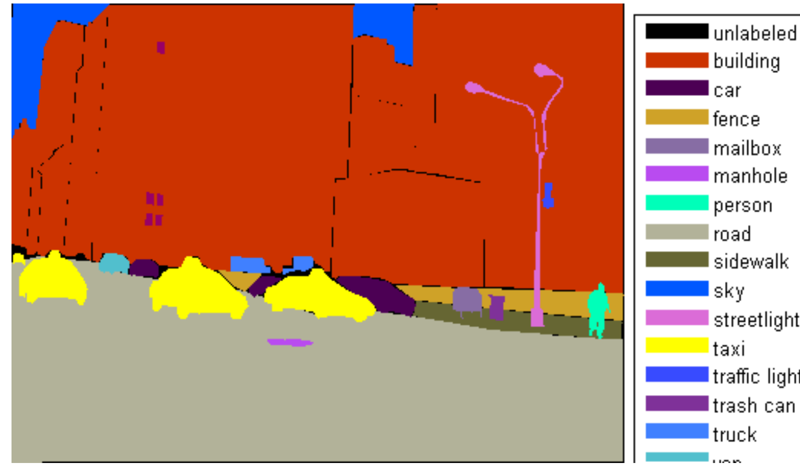
Human Annotation



Tighe CVPR13

Scene Parsing | Semantic Segmentation Results

Image

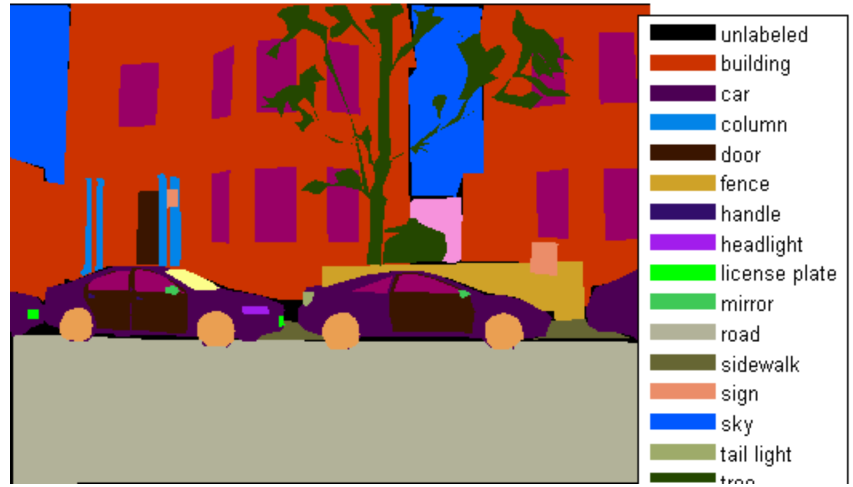


Human Annotation

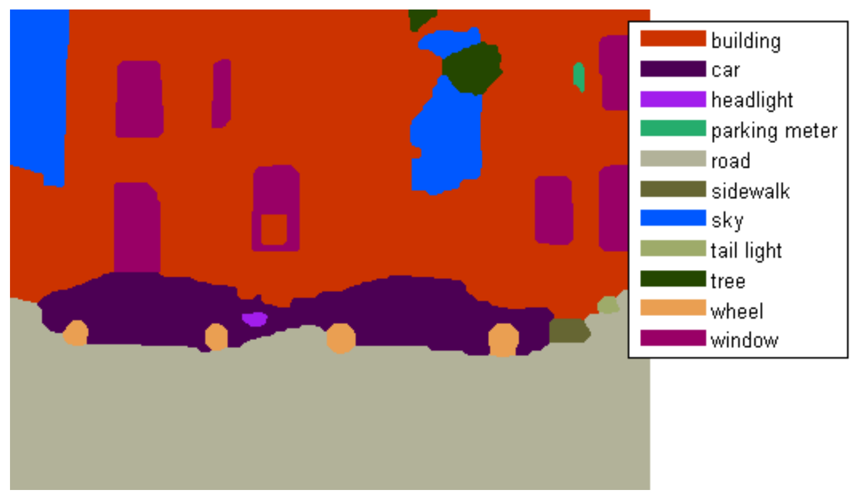
Tighe CVPR13

Scene Parsing | Semantic Segmentation Results

Image



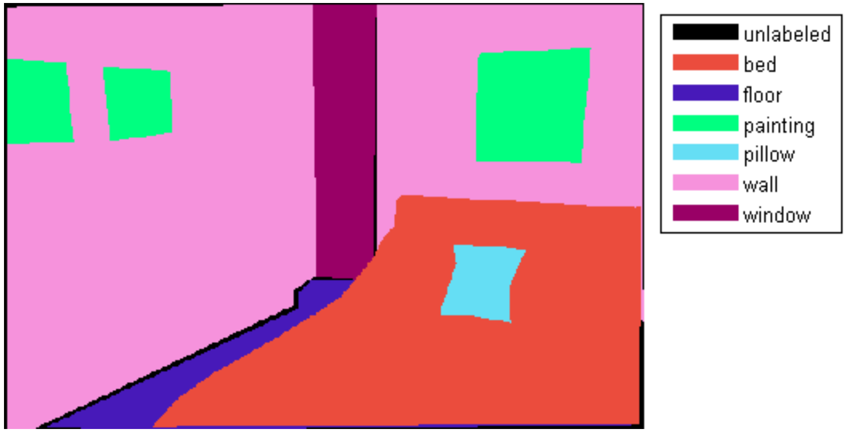
Human Annotation



Tighe CVPR13

Scene Parsing | Semantic Segmentation Results

Image



Human Annotation

Tighe CVPR13

Adobe

Summary and Conclusion

- There are many variations of segmentation problems
  - How many classes? What are the classes?
  - What features are used?
  - Hard or Soft Segmentation?
  - Automatic or Interactive? What User Input?
  - How many images are segmented?

- Semantic Segmentation: still a lot of work to be done

Adobe