SHADOW-FREE SEGMENTATION IN STILL IMAGES USING LOCAL DENSITY MEASURE

Aleksandrs Ecins, Cornelia Fermüller
and Yiannis Aloimonos

University of Maryland Computer Vision Lab

May 2, 2014

GREETINGS FROM MARYLAND!

OUTLINE

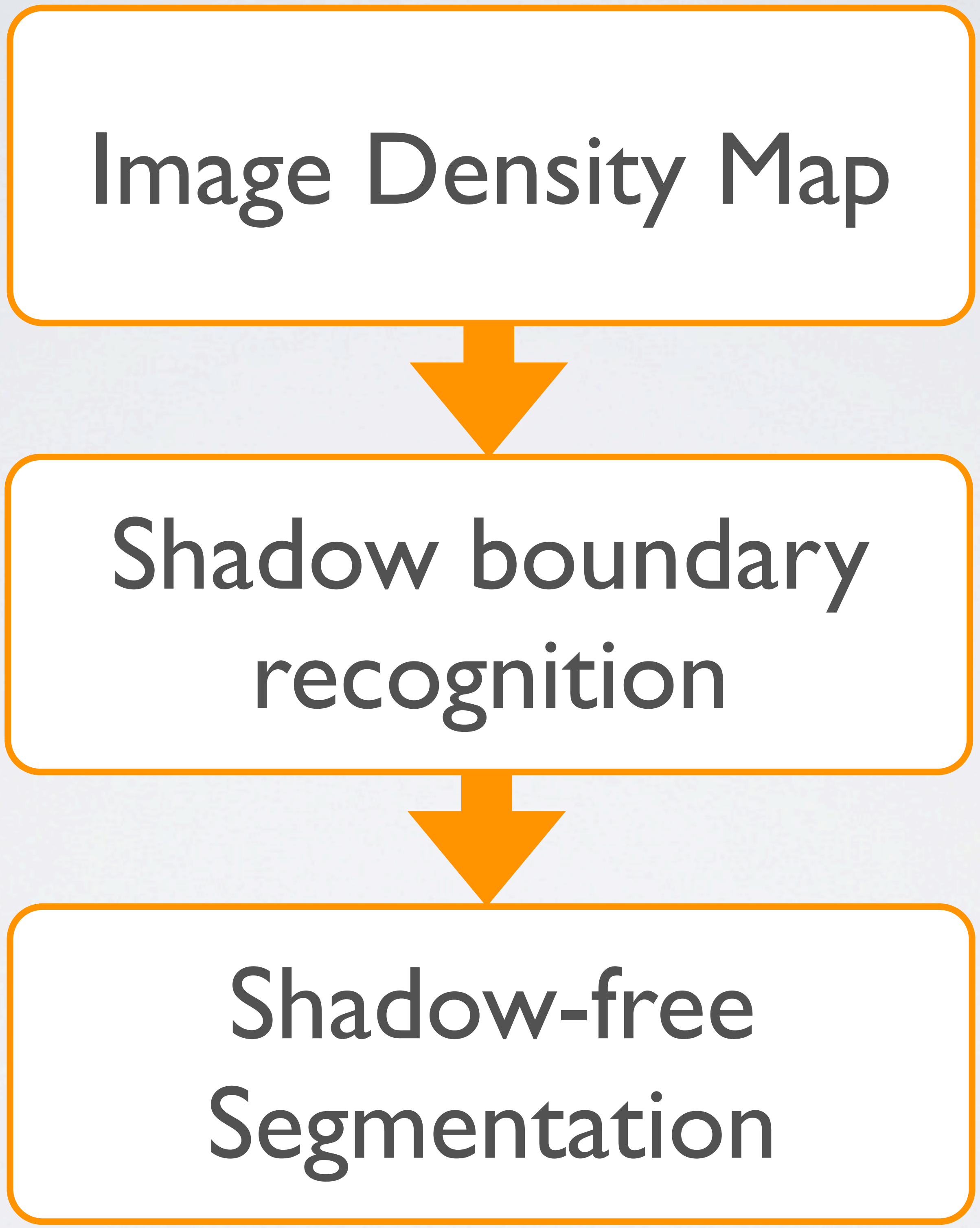


Image Density Map
Shadow boundary recognition
Shadow-free Segmentation

SHADOW MODEL

SHADOW MODEL

- Shadow model:

$$\mathcal{I}_k(\mathbf{x}) = \mathcal{R}_k(\mathbf{x}) \cdot \mathcal{L}_k(\mathbf{x}) \cdot \mathcal{C}_k(\mathbf{x})$$

- Assumption:

$\mathcal{C}_k(\mathbf{x})$ is piecewise-constant

- Appearance changes:

intensity	decreased
colour	no change
texture	no change

SHADOWS AND TEXTURE

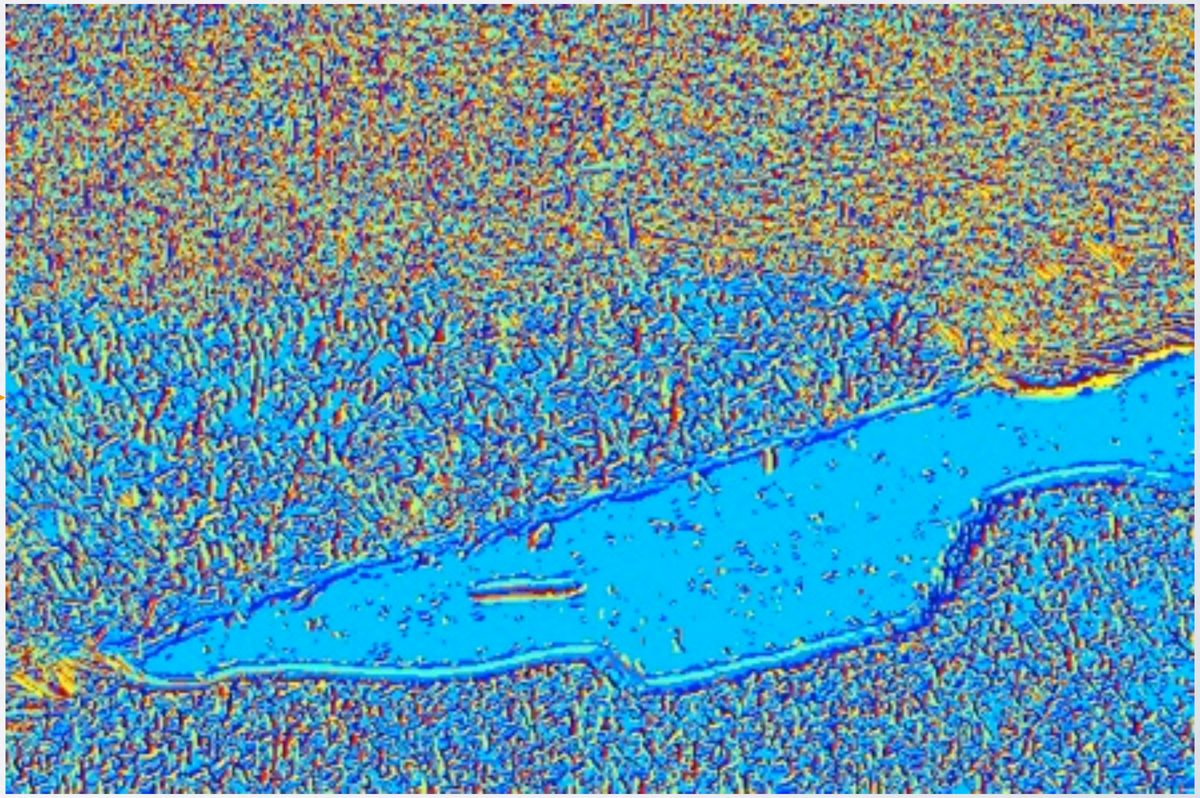
- Standard approach to texture description [Malik et. al]:

    1. Filter image with a filterbank
    2. Cluster filter responses into textons
    3. Assign each pixel to its closest texton

SHADOWS AND TEXTURE

- Standard approach to texture description [Malik et. al]:

1. Filter image with a filterbank
2. Cluster filter responses into textons
3. Assign each pixel to its closest texton



SHADOWS AND TEXTURE

Problem:
Lower energy textons are clustered together

$$f * (c \cdot I) = c \cdot (f * I)$$

Solution:
Preprocess image by computing its density map

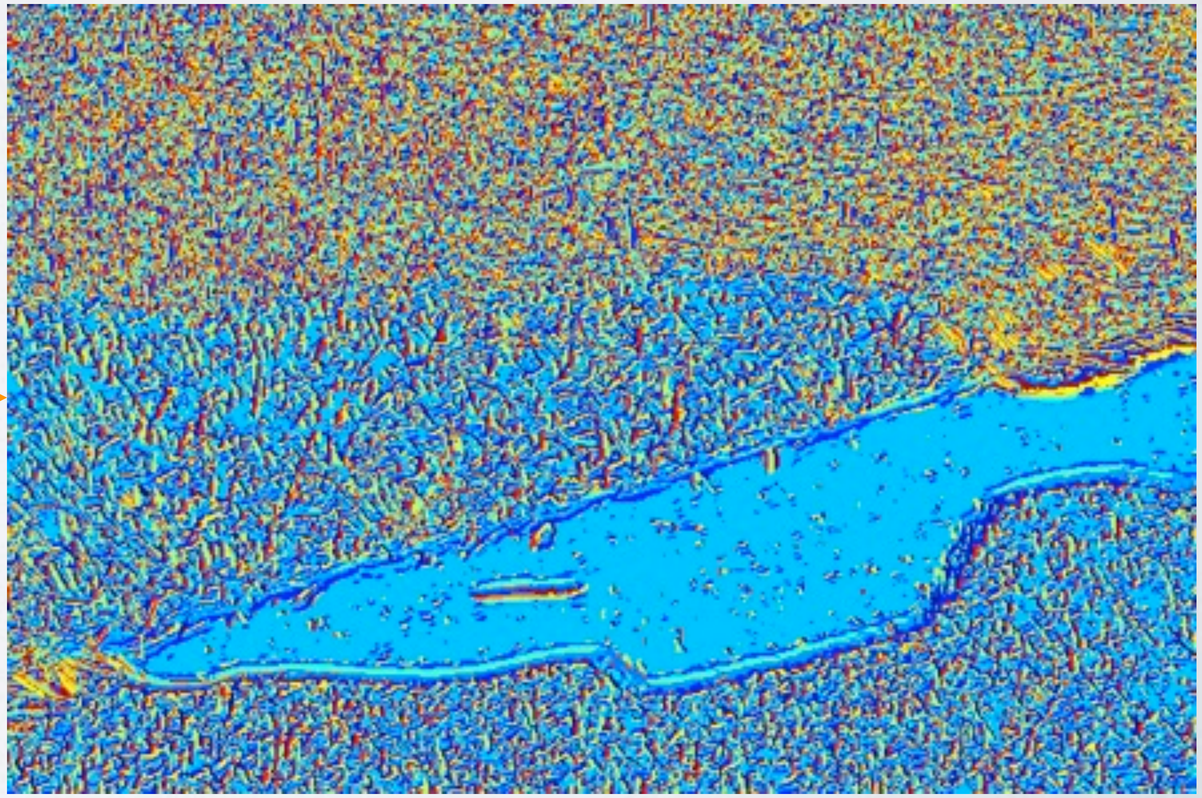


IMAGE DENSITY MAP

- Define a measure function on the image over a radius

$$\mu(\mathbf{x}, r) = \sum_{\|\mathbf{y}-\mathbf{x}\| \leq r} I(\mathbf{y})$$

- Hypothesize that it varies as an exponential of the radius

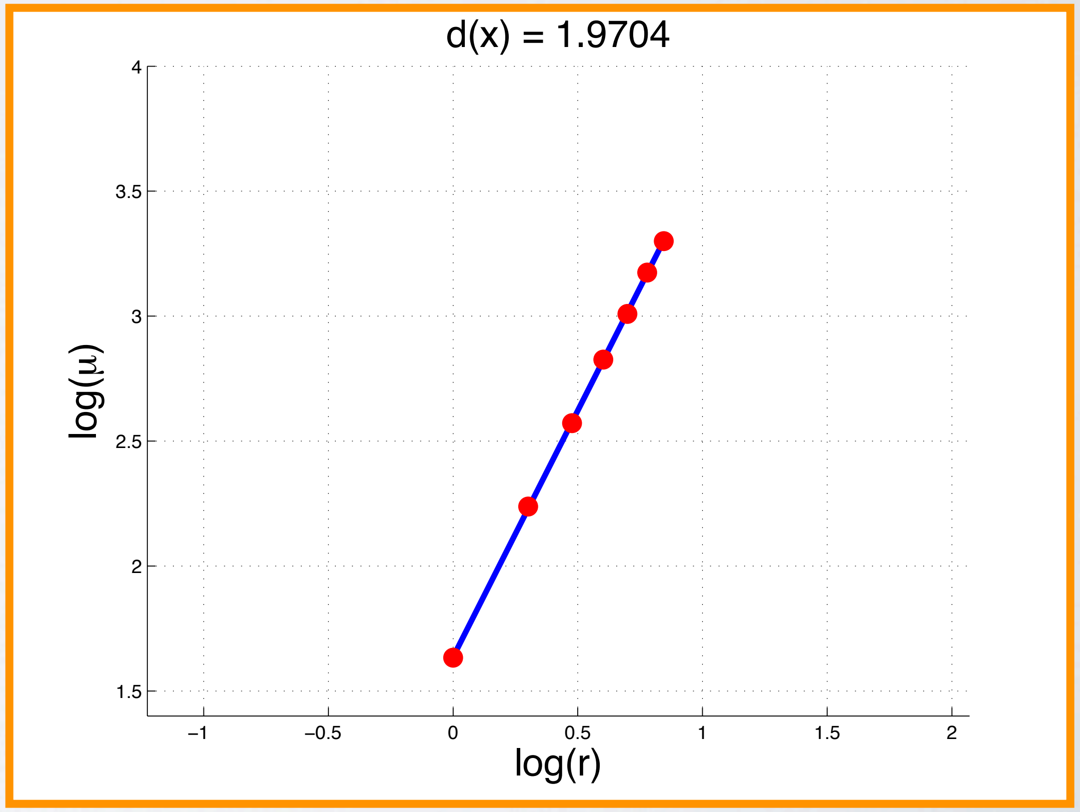
$$\mu(\mathbf{x}, r) = kr^{d(\mathbf{x})}$$
$$\log(\mu(\mathbf{x}, r)) = \log k + d(\mathbf{x}) \log r$$

- $d(\mathbf{x})$ is the local density measure at pixel $\mathbf{x}$

ESTIMATING LOCAL IMAGE DENSITY

- Take measurements at multiple scales
- Solve a linear system of equations
- This corresponds to fitting a line to n points

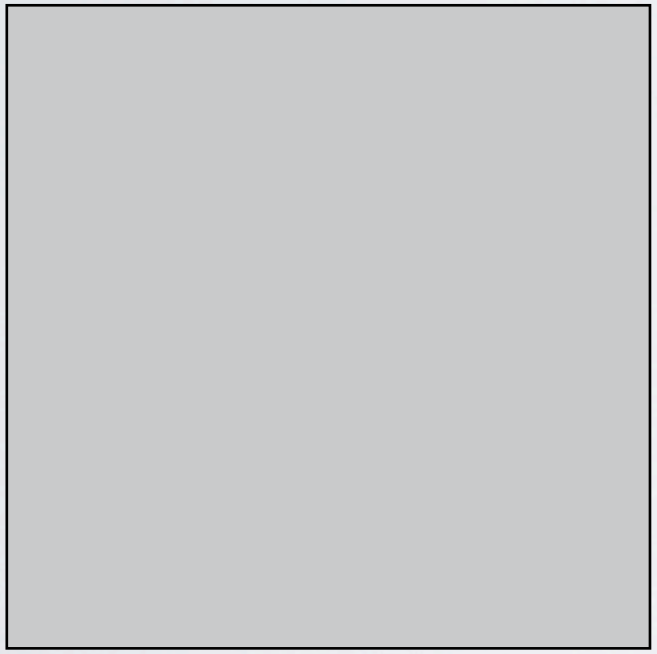
$$
\begin{aligned}
\log(\mu(\mathbf{x}, r_1)) &= \log k + d(\mathbf{x}) \log r_1 \\
\log(\mu(\mathbf{x}, r_2)) &= \log k + d(\mathbf{x}) \log r_2 \\
&\vdots \\
\log(\mu(\mathbf{x}, r_n)) &= \log k + d(\mathbf{x}) \log r_n
\end{aligned}
$$



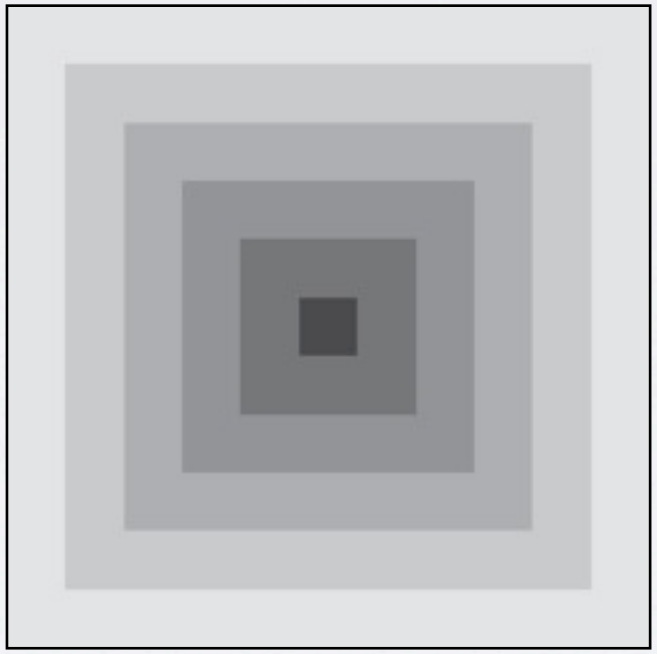
DENSITY INTUITION

- Intuitively density measures the degree of regularity in intensity variation in a neighborhood around point $\mathbf{x}$

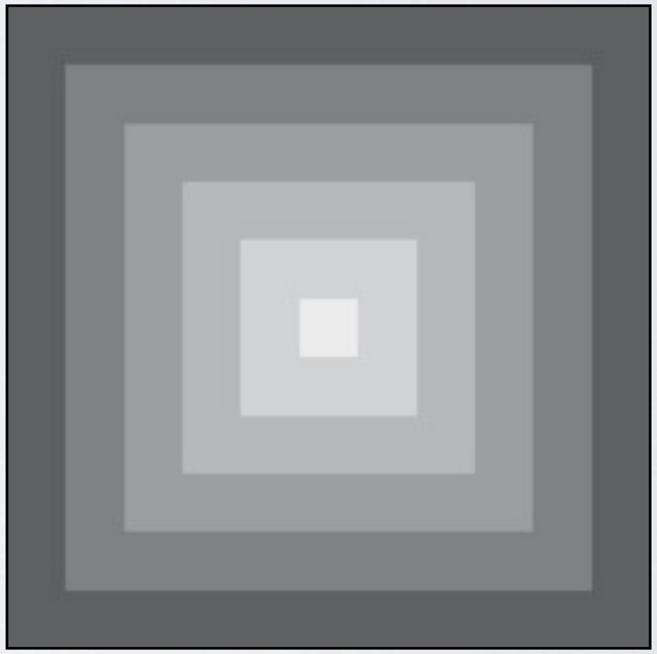
$$\mu(\mathbf{x}, r) = kr^{d(\mathbf{x})}$$



$d(\mathbf{x}) = 2.0$



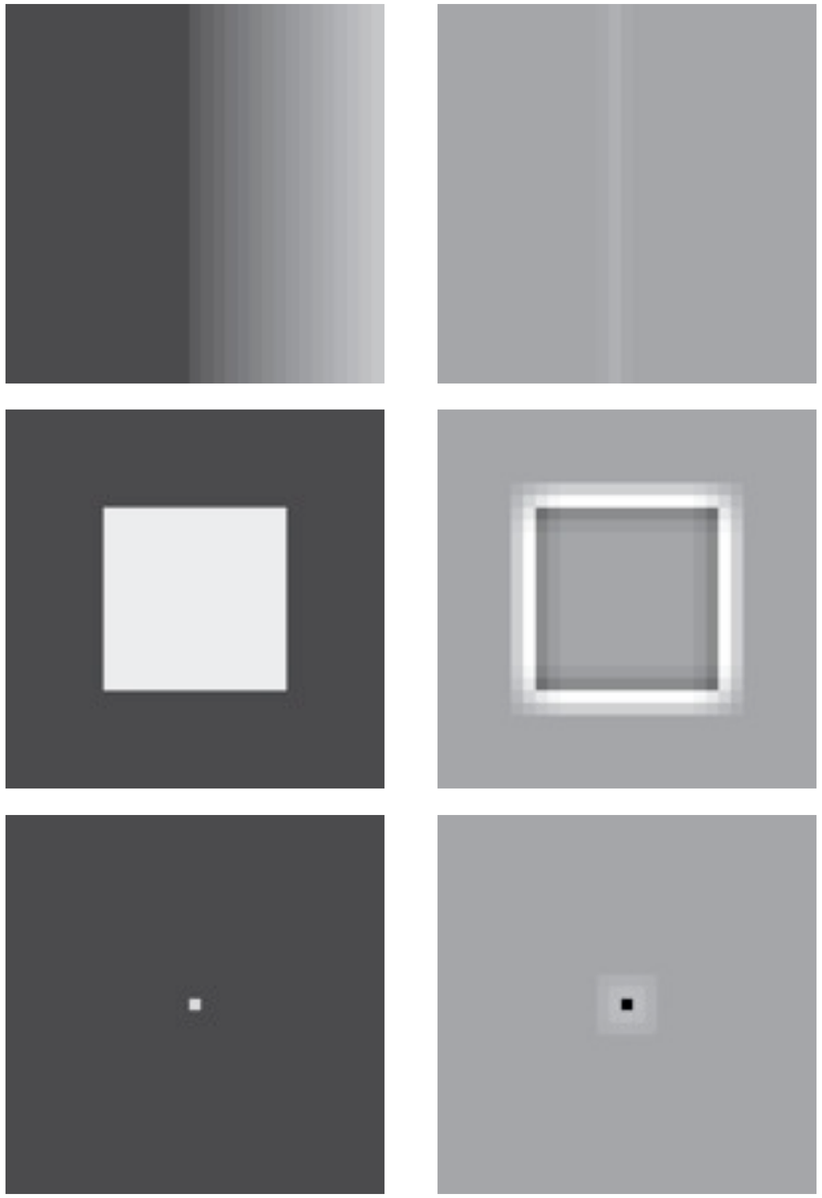
$d(\mathbf{x}) = 2.7$



$d(\mathbf{x}) = 1.83$

IMPORTANT PROPERTIES OF THE DENSITY MAP

Preserves textural features



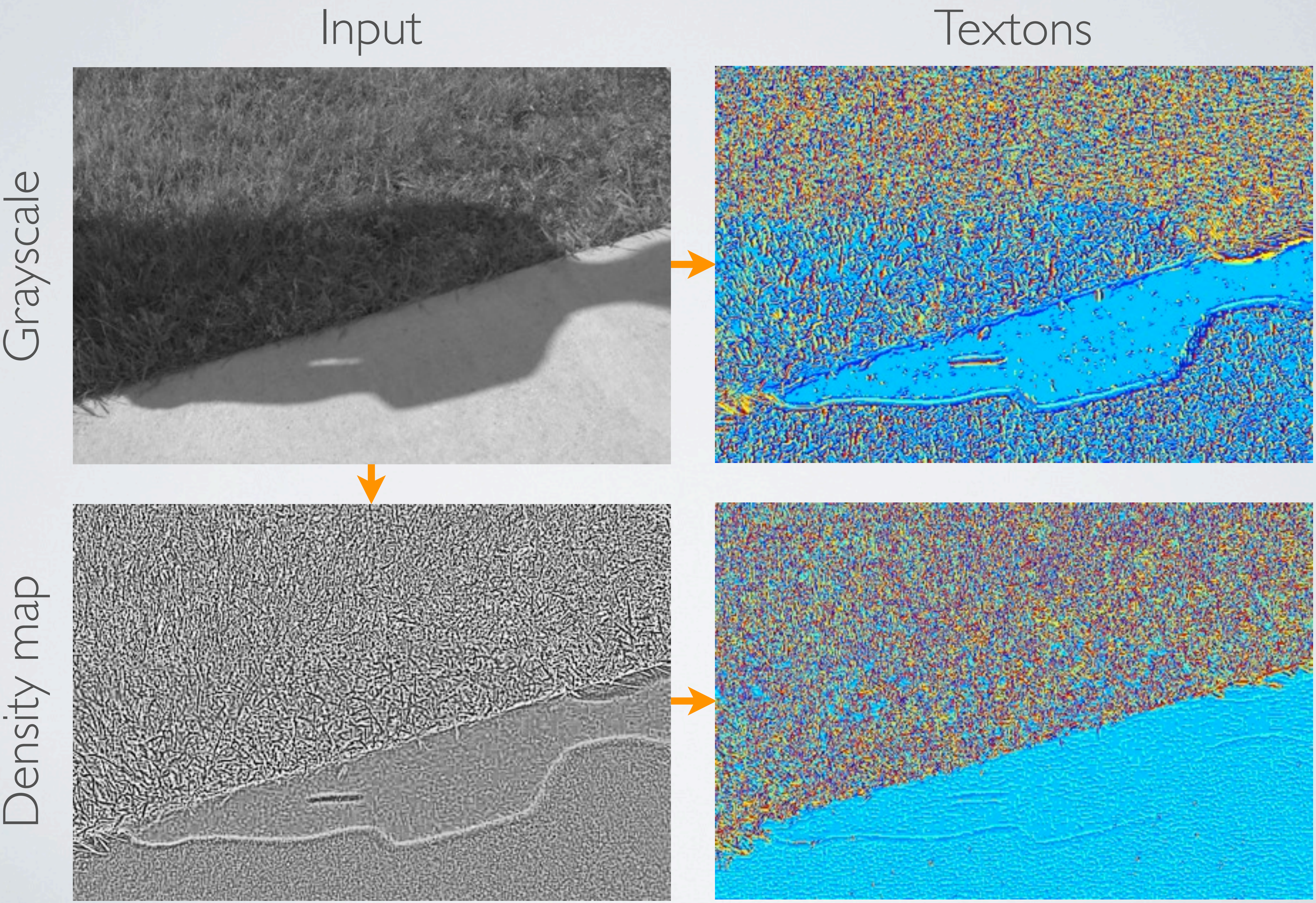
Intensity Density

Invariant to local multiplicative changes to intensity

$$\alpha\mu(\mathbf{x}, r) = \sum_{\|\mathbf{y}-\mathbf{x}\| \leq r} \alpha I(\mathbf{y})$$

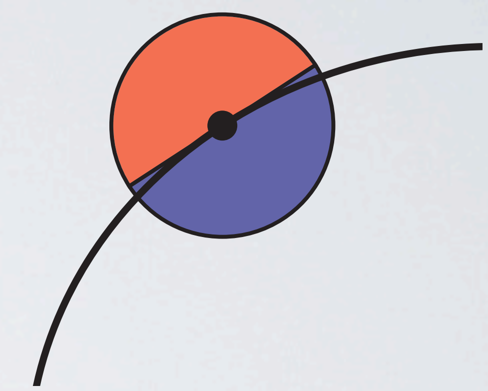
$$\alpha\mu(\mathbf{x}, r) = \alpha k r^{d(\mathbf{x})}$$

APPLICATION TO TEXTURE DESCRIPTION



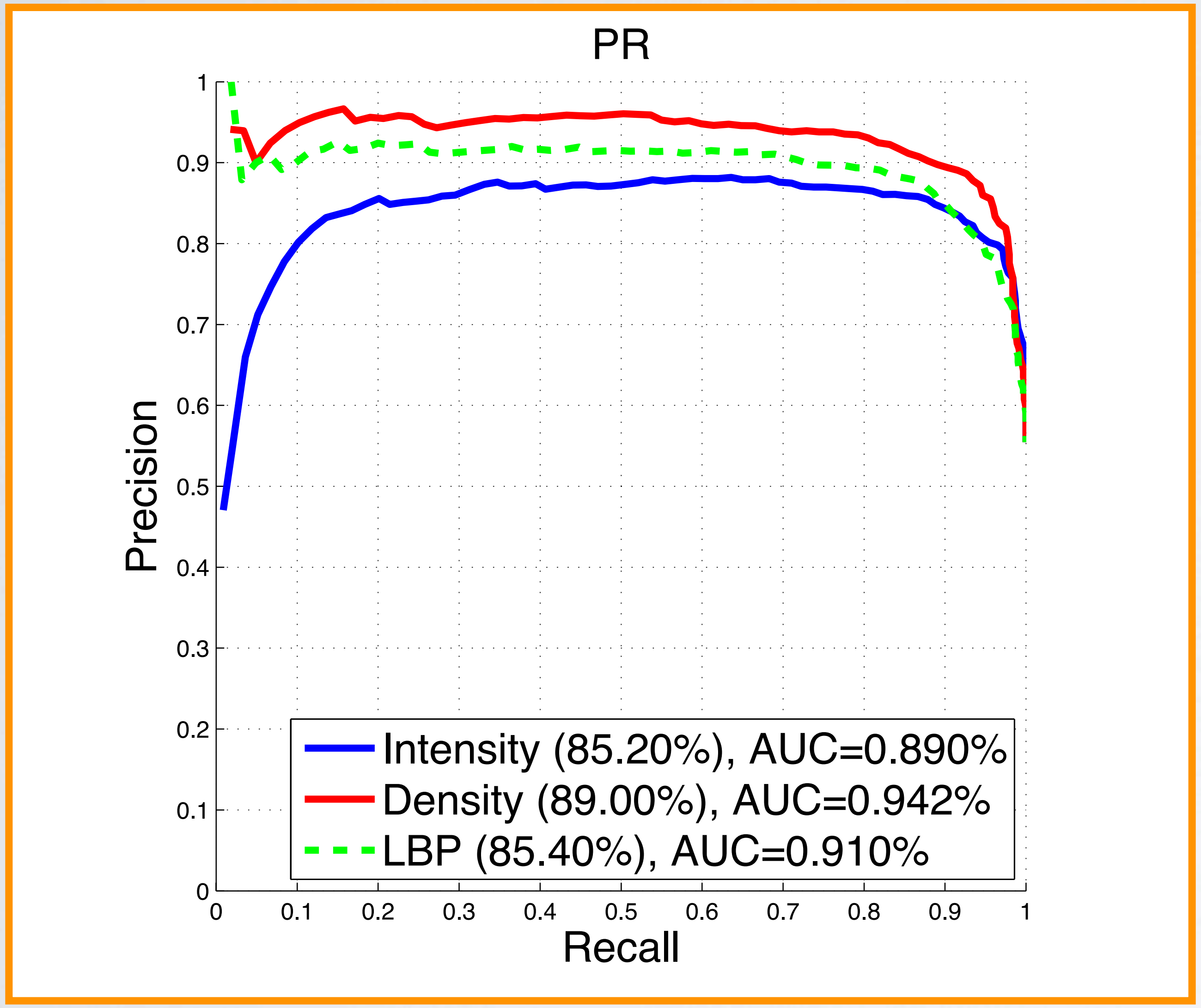
SHADOW BOUNDARY DETECTION

- Goal: given a boundary in an image recognize if it is a shadow boundary
- Compare appearance features across boundary [Lalonde et. al]
- Shadow detection dataset of Zhu et. al

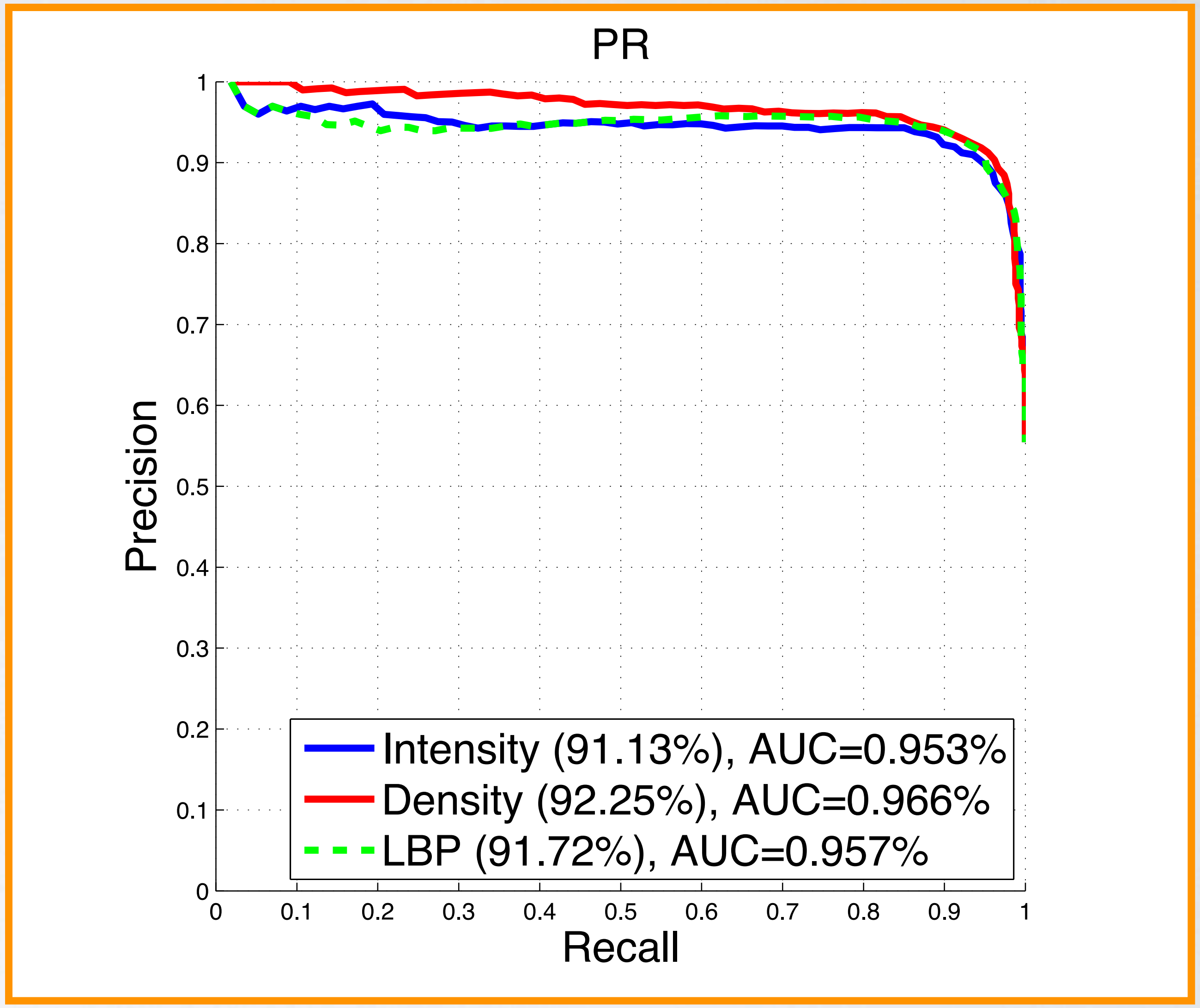


<table>
<tr><td>intensity</td><td>intensity ratio</td></tr>
<tr><td>colour</td><td>RGB colour channel ratios</td></tr>
<tr><td rowspan="3">texture</td><td>intensity textons</td></tr>
<tr><td>Local Binary Patters (LBP)</td></tr>
<tr><td>density textons</td></tr>
</table>

SHADOW DETECTION RESULTS



Grayscale



Colour

SHADOW-FREE SEGMENTATION

FOREGROUND-BACKGROUND SEGMENTATION

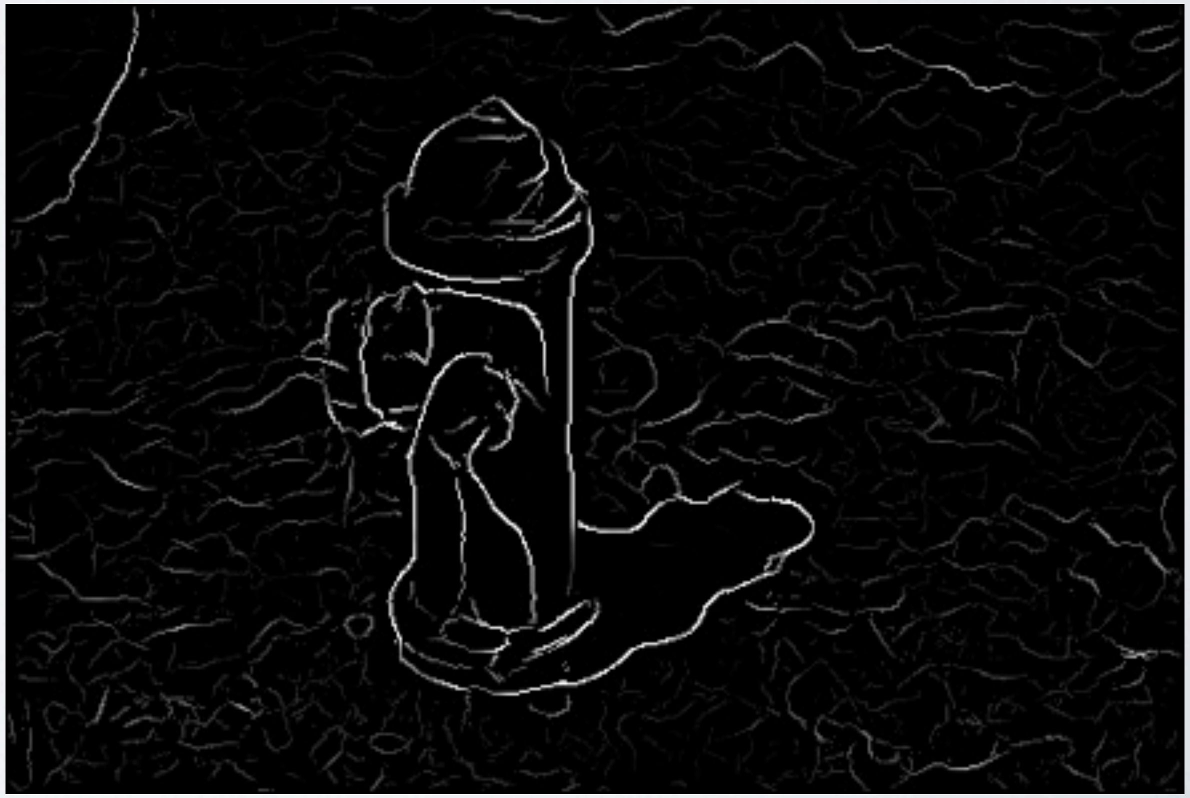
- Graph-cut approaches to foreground-background segmentation find a labeling f that minimizes

$$E(f) = \sum_{p \in \mathcal{P}} D_p(f_p) + \lambda \sum_{\{p,q\} \in \mathcal{N}} V_{p,q} \cdot \delta(f_p \neq f_q)$$

- $D_p(f_p)$ measures how likely a pixel belongs to BG or FG
  - Uses a colour model
- $V_{p,q}$ measures the likelihood of two adjacent pixels belonging to the same class
  - Uses image gradients

EFFECTS OF SHADOWS ON SEGMENTATION

- Introduces strong gradients and the boundary of shadow regions
- Reduces gradients in shadowed regions



SEGMENTATION ERRORS

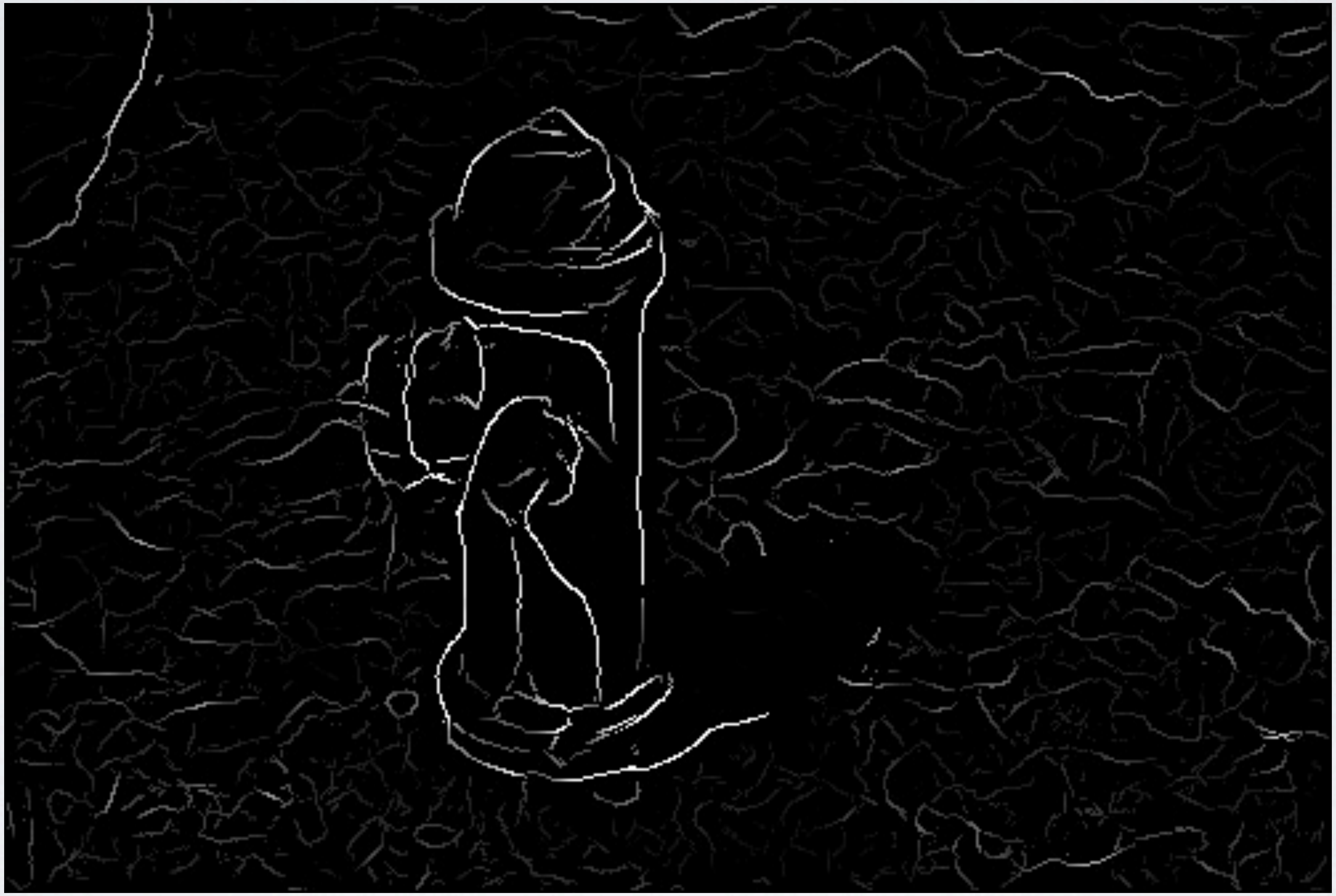
Oversegmentation due to strong self-shadow

Undersegmentation due to strong cast shadow and weakened edge between object and shadow

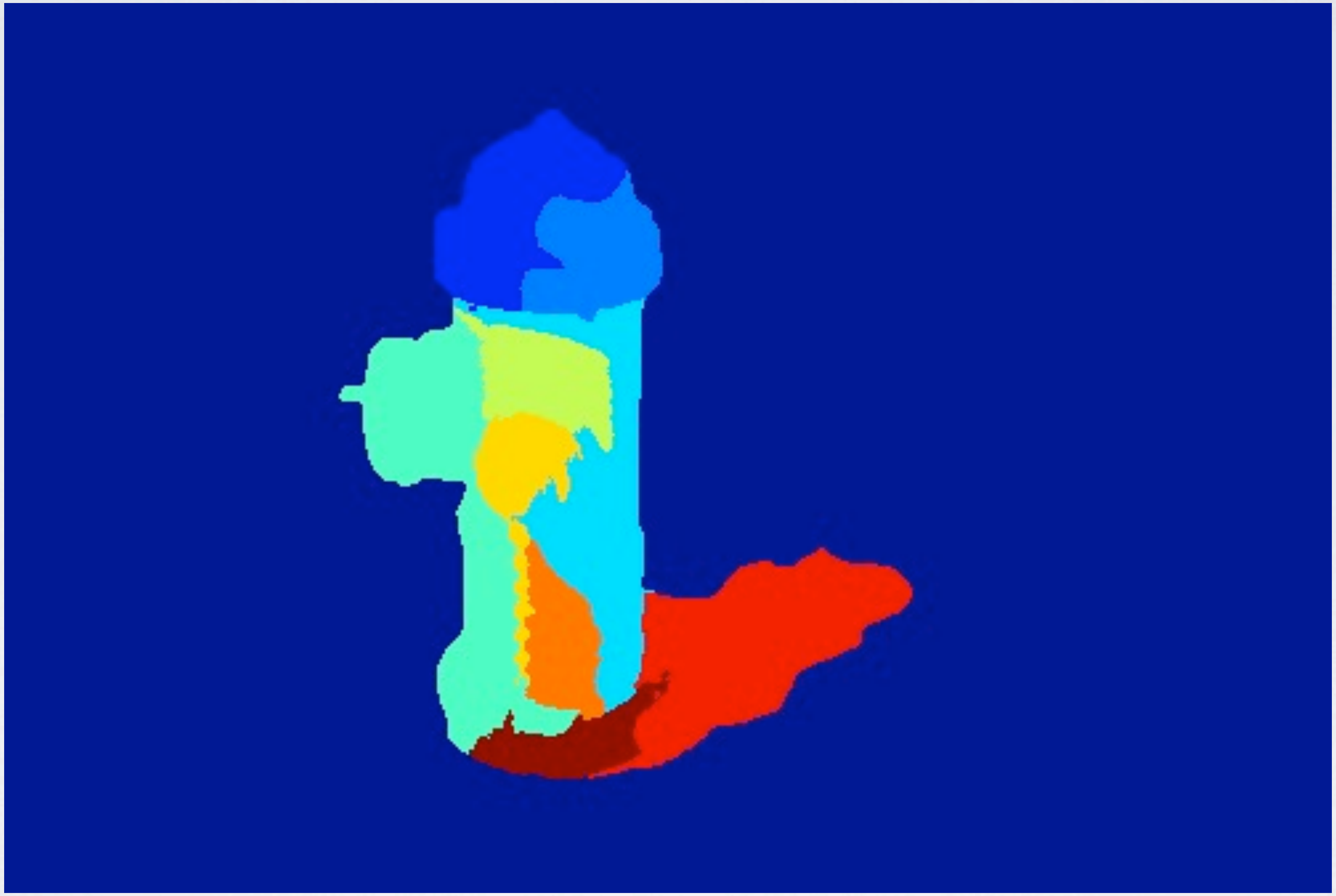
STEP 1: SEGMENT

STEP 2: DETECT SHADOWS

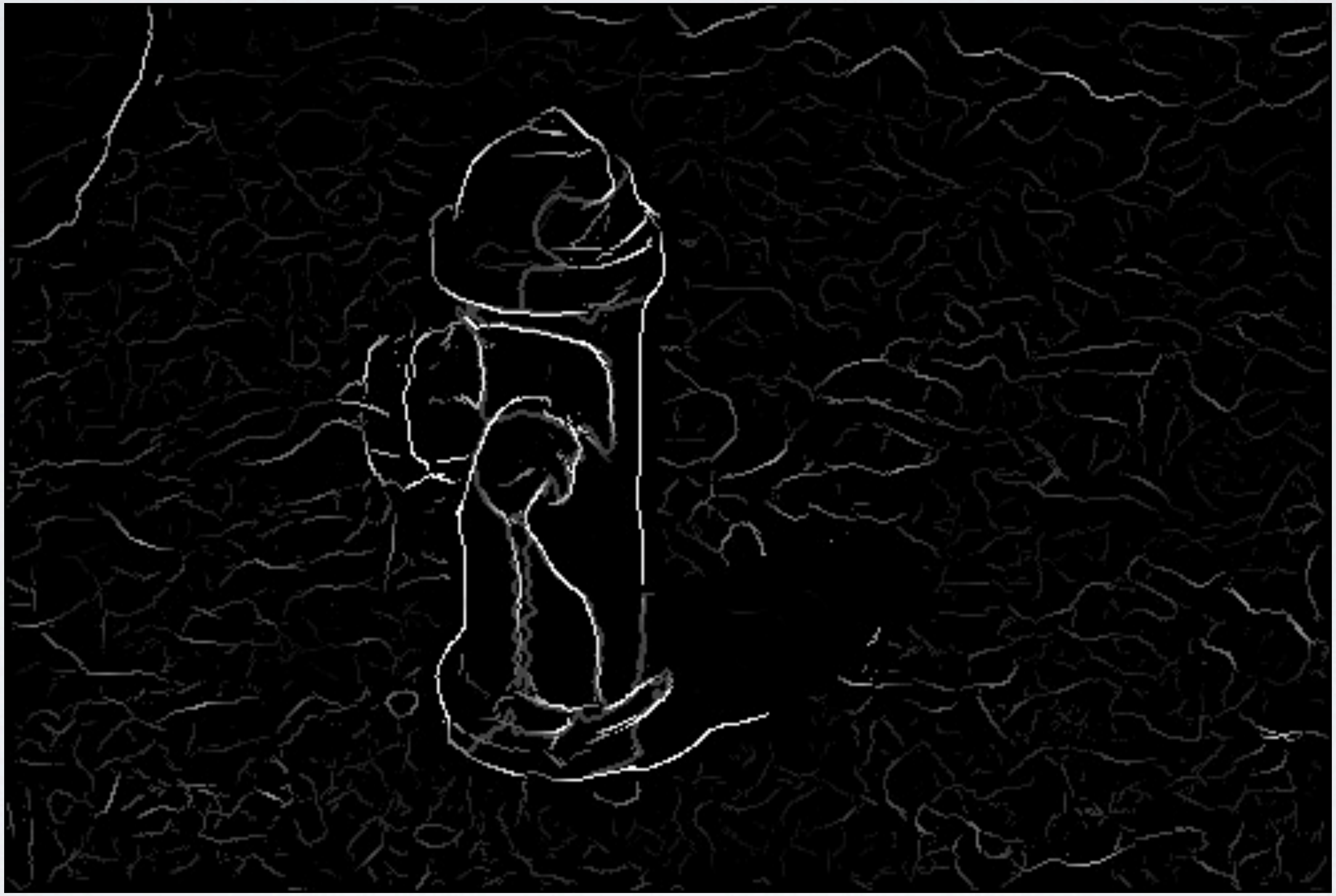
STEP 3: ATTENUATE STRONG SHADOW EDGES



STEP 4: OVERSEGMENT THE SEGMENTATION AREA



STEP 5: ADD EDGES BETWEEN SEGMENTS



STEP 6: SEGMENT AGAIN

QUANTITATIVE EVALUATION

- Dataset of 53 outdoor images of objects affected by shadows

- Groundtruth segmentation and segmentation initialization for each image

Input | Groundtruth | Input | Groundtruth

QUANTITATIVE EVALUATION

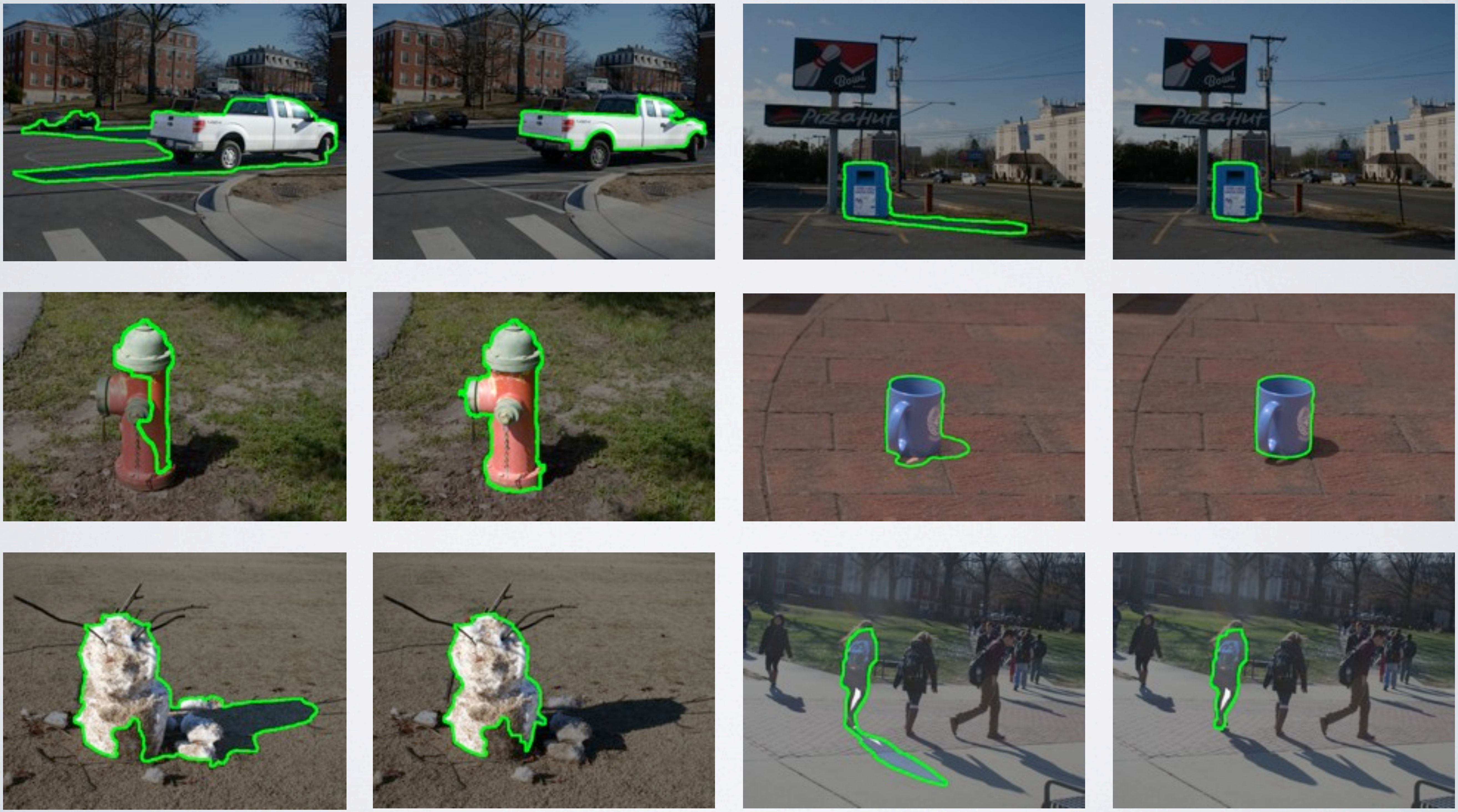
- Compared four algorithms:

    1. Baseline: original segmentation code
    2. Shadow-free segmentation with intensity textons
    3. Shadow-free segmentation with LBP
    4. Shadow-free segmentation with density textons

Algorithm	F-measure
Baseline	0.77±0.027
Intensity textons	0.81±0.036
LBP	0.82±0.039
Density textons	**0.84±0.033**

EXAMPLES

Baseline | Shadow-free | Baseline | Shadow-free



FAILURE EXAMPLES

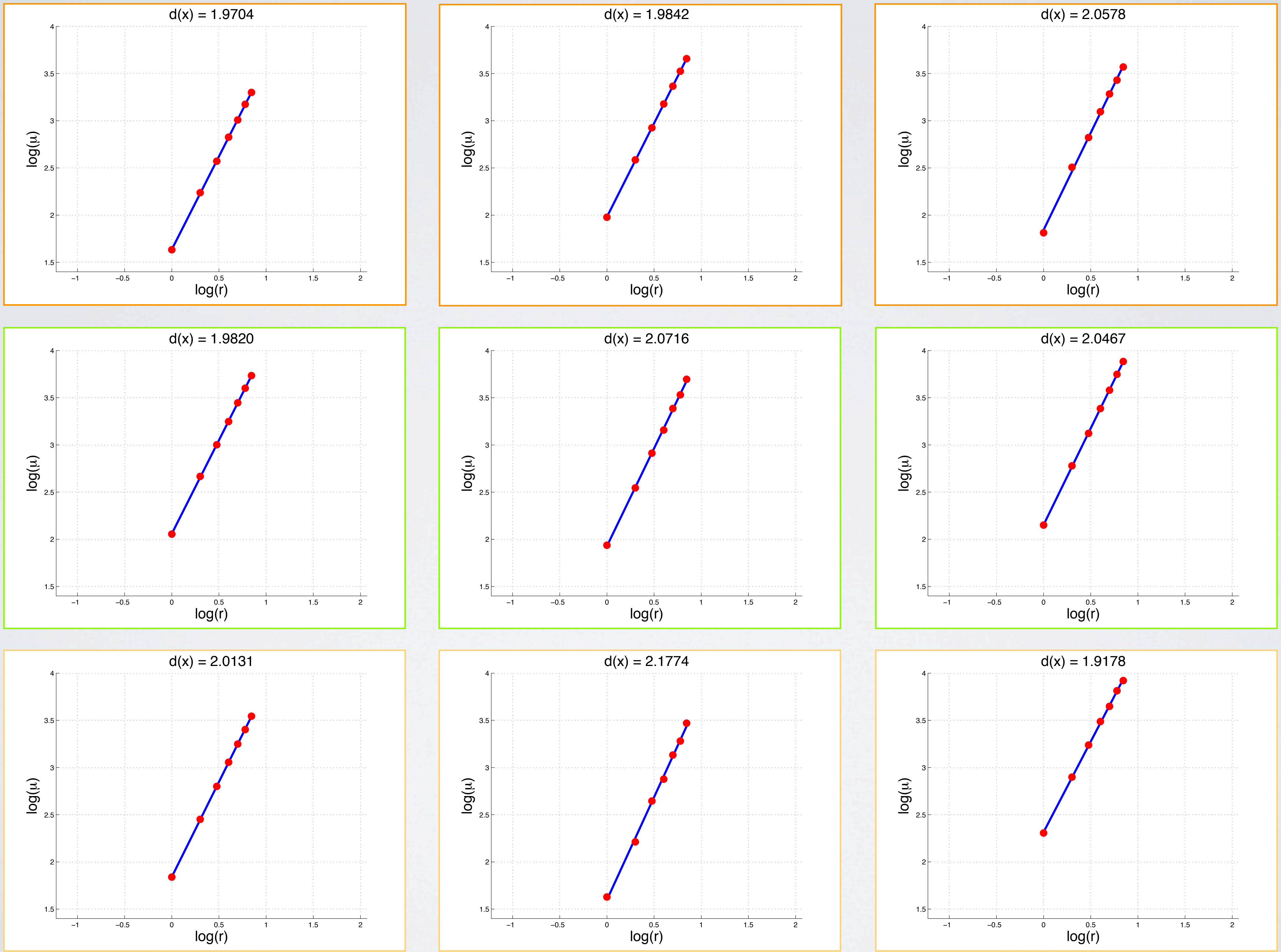
Baseline | Shadow detection | Shadow-free

THANKS FOR YOUR ATTENTION

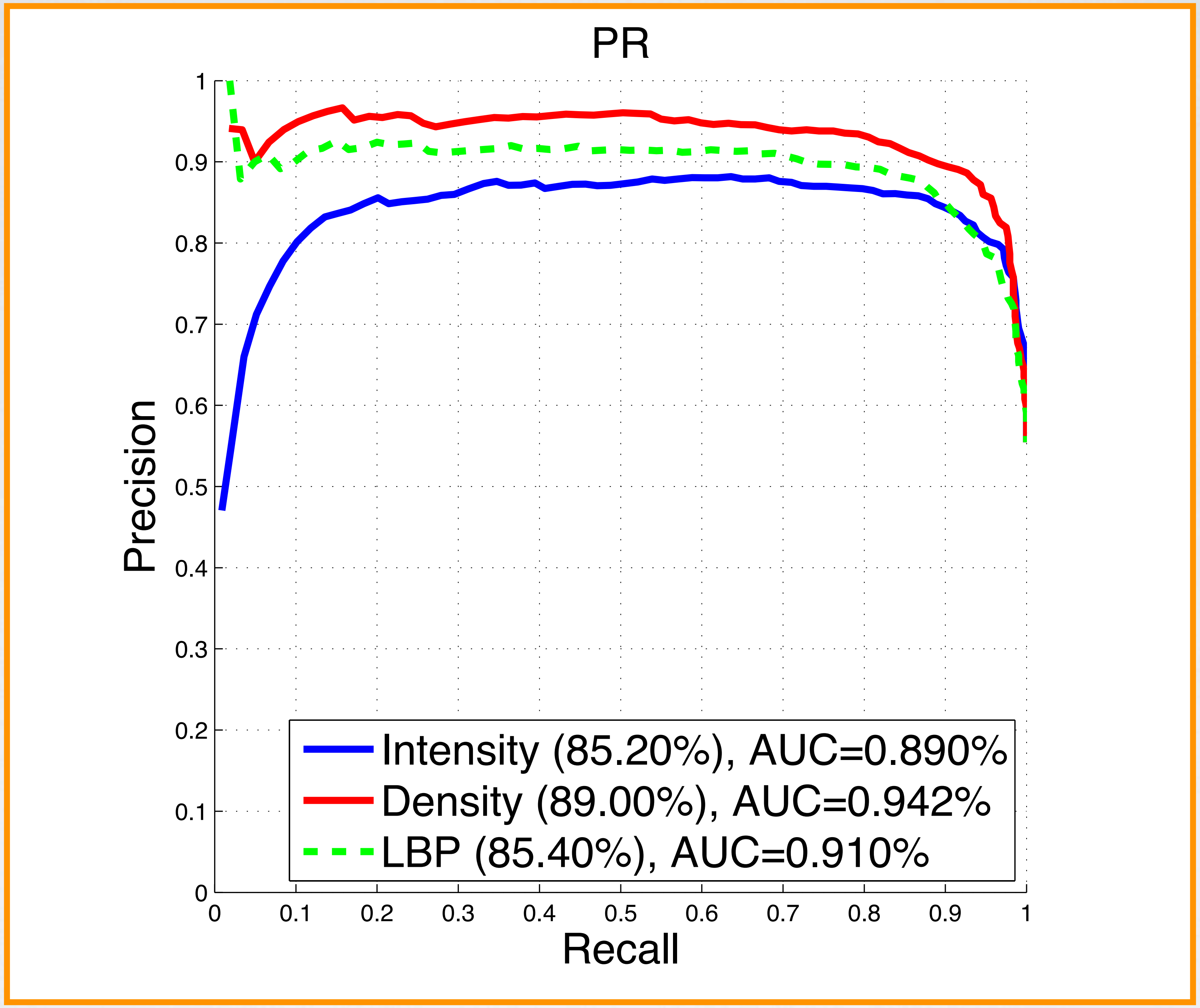
Questions?

Code available online at www.umiacs.umd.edu/~aecins/

LOCAL DENSITY ESTIMATION EXAMPLES

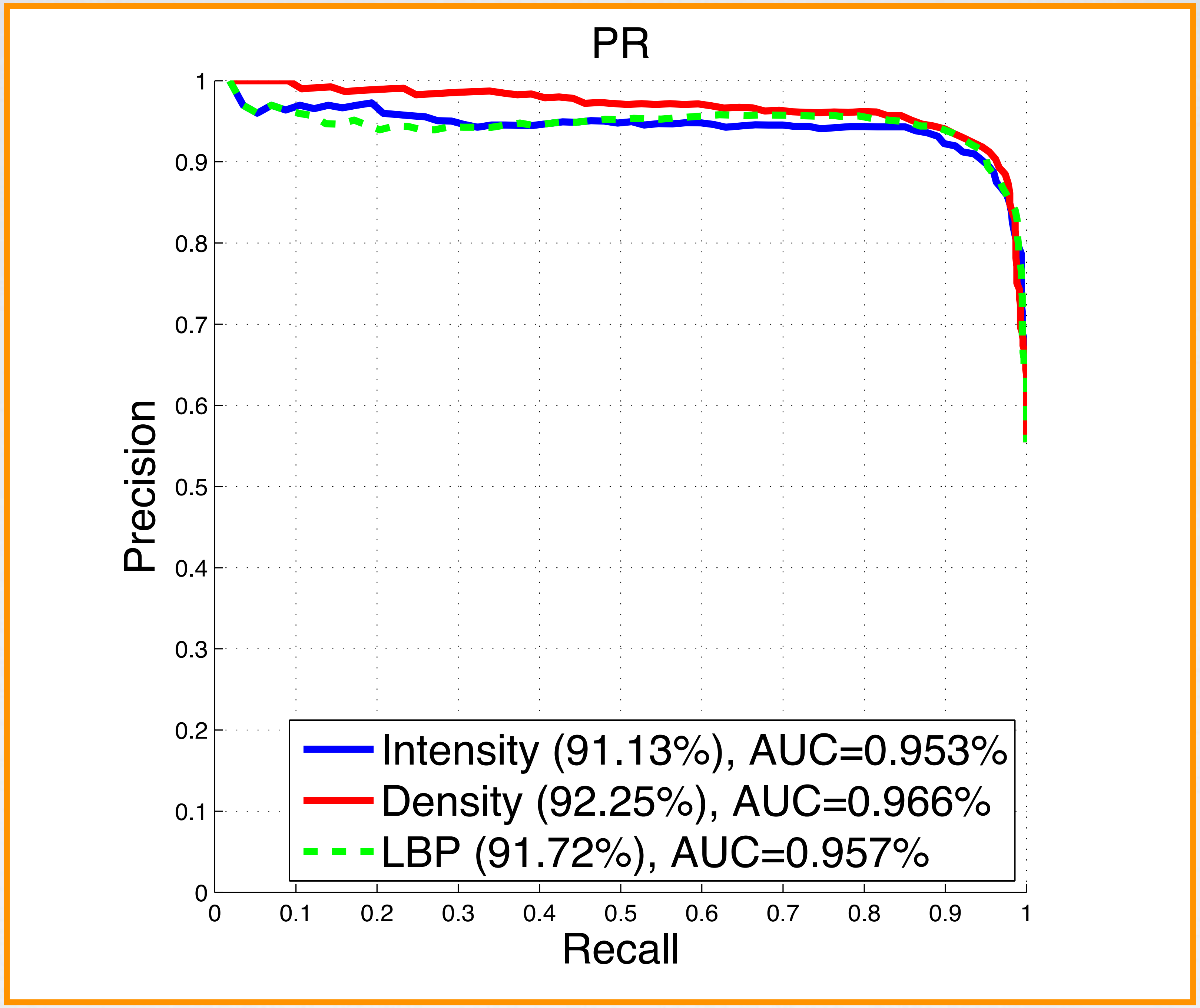


SHADOW DETECTION



Grayscale

SHADOW DETECTION



Colour