

Saliency: What do you look at in an image?

Students Reading Group

2016

by

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Outline

- Introduction
- Motivation
- Superpixel based approach
- Results & Discussions

Introduction

- What stands out in every image?



Image courtesy: HFT dataset

Introduction

- What stands out in every image?

Butterfly



Flower



Green apple



Red apple



Image courtesy: HFT dataset

Definition

- Saliency: measure of feature distinctness of regions or objects in images
- Salient objects
 - capture attention
 - distinctive in color or spatial features



Input image

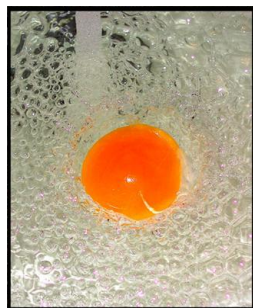


Salient object

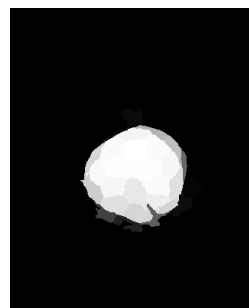
Image courtesy: MSRA dataset

Saliency map

- Saliency map: a saliency value assigned to each pixel



Input image



Saliency map

Image courtesy: MSRA dataset

Saliency map

- Saliency map: a saliency value assigned to each pixel



Input image

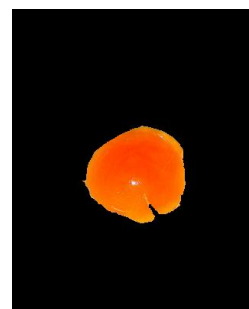


Saliency map

- Salient objects: saliency map is thresholded to obtain salient objects



Thresholded saliency (binary)



Salient object

Result from Zhu *et al.*, CVPR 2014

Image courtesy: MSRA dataset

Motivation

- Applications
 - Object segmentation
 - Video summarization
 - Region-of-interest image compression
 - Image and video quality assessment
- Large image databases and long videos
- Only the important parts are processed
- Reduction in complexity

Typical approaches

- Local approach (center-surround window)
 - Pixel based method [... initial works ...]
- Global approach (global comparison)
 - Superpixel based method [... several works ...]
 - Patch based method [... several works ...]
- Frequency domain method [... a small volume of works ...]

Typical approaches

- Local approach (center-surround window)
 - Pixel based method [... initial works ...]
- **Global** approach (global comparison)
 - **Supapixel based method** [... several works ...]
 - Patch based method [... several works ...]
- Frequency domain method [... a small volume of works ...]

Zhu, Wangjiang, Shuang Liang, Yichen Wei, and Jian Sun. "Saliency optimization from robust background detection." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2814-2821. 2014.

Superpixel segmentation

- Segment the image into superpixels



Input image

Image courtesy: Li *et al.* 2011

Superpixel segmentation

- Segment the image into superpixels



Superpixel segmentation

Superpixel boundary is shown in green

Superspixel segmentation

- Segment the image into superspixels
 - group of pixels
 - contains pixels of uniform color
 - retain object boundary unlike rectangular patches



Superspixel segmentation

Superspixel boundary is shown in green

Superspixel segmentation

- Segment the image into superspixels
 - group of pixels
 - contains pixels of uniform color
 - retain object boundary unlike rectangular patches
- Compute features (vectors) for every superspixel
 - color mean
 - color histogram



Superspixel segmentation

Superspixel boundary is shown in green

Saliency of superpixels

- Compute saliency value of every superpixel and assign it to pixels inside it



Superpixel segmentation

Saliency of superpixels

- Saliency value of this superpixel should be *large*



Superpixel segmentation

Saliency of superpixels

- Saliency value of this superpixel should be *large*



Superpixel segmentation

Saliency of superpixels

- Saliency value of this superpixel should be ***small***



Superpixel segmentation

Saliency of superpixels

- Saliency value of this superpixel should be *small*



Superpixel segmentation

Notations

- A superpixel v_i
- **Spatial** distance between two superpixels v_i and v_j is $d_s(v_i, v_j)$



Notations

- A superpixel v_i
- **Feature** distance between two superpixels v_i and v_j is $d_f(v_i, v_j)$



Notations

- A superpixel v_i
- **Spatial** distance between two superpixels v_i and v_j is $d_s(v_i, v_j)$
- **Feature** distance between two superpixels v_i and v_j is $d_f(v_i, v_j)$
- **Geodesic** distance between two superpixels v_i and v_j is $d_g(v_i, v_j)$
- **Saliency** value of a superpixel v_i is $\mathcal{S}(v_i)$

Saliency computation

- 'Global' method
- Saliency value of a superpixel



Saliency computation

- ‘Global’ method
- Saliency value of a superpixel is the sum of its feature distances with the rest of the superpixels in the image

$$\mathcal{S}(v_i) = \sum_{j=1}^N d_f(v_i, v_j)$$

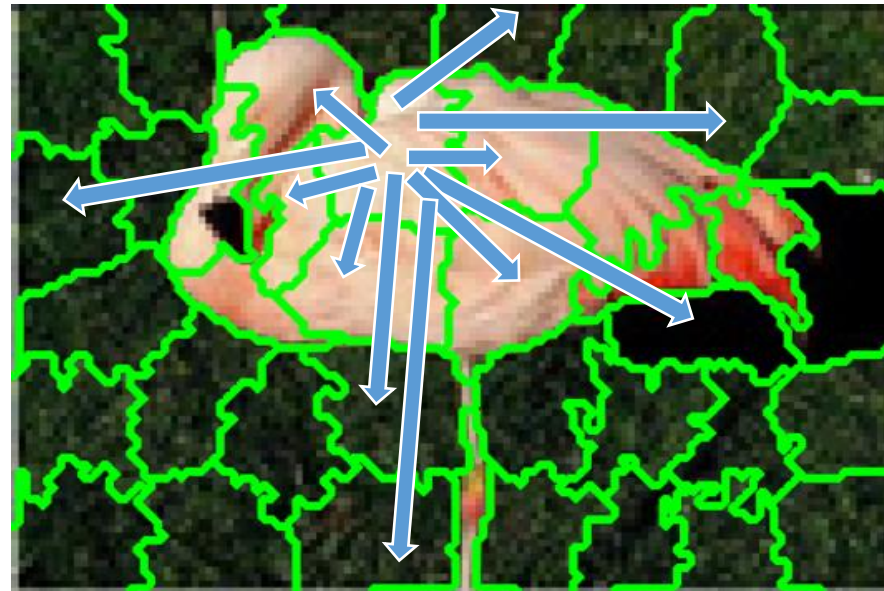


Saliency computation

- Incorporate 'local' contrast
- We want to give more importance to nearer superpixels

$$\mathcal{S}(v_i) = \sum_{j=1}^N d_f(v_i, v_j)$$

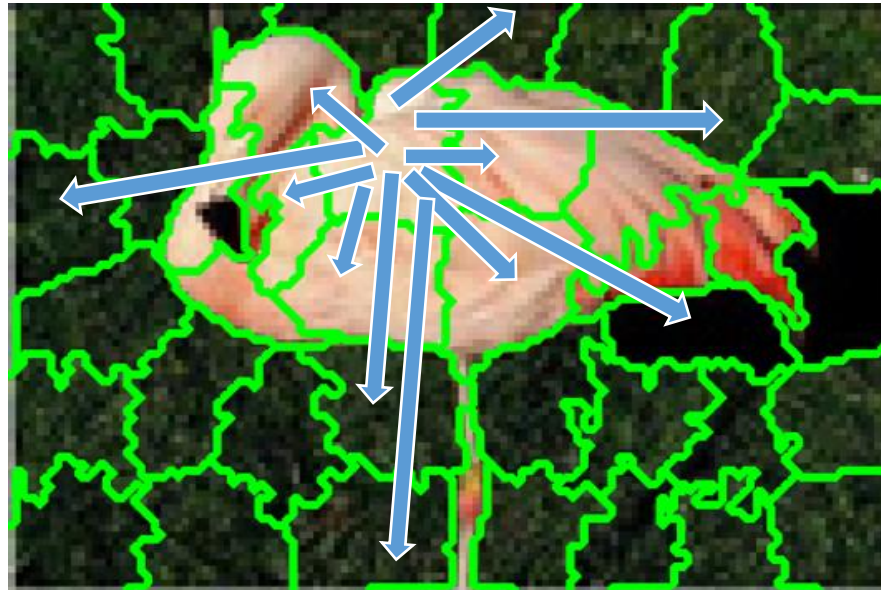
Feature
distance



Saliency computation

- Incorporate 'local' contrast
- We want to give more importance to nearer superpixels

$$\mathcal{S}(v_i) = \sum_{j=1}^N \overset{\text{Feature distance}}{d_f(v_i, v_j)} \exp\left(-\frac{1}{2\sigma_1^2} \left(\overset{\text{Inverse of spatial distance}}{d_s(v_i, v_j)}\right)^2\right)$$



Background information

- Add semi-supervision
- Use background information
- For every superpixel, find its probability of belonging to background
 - i.e. not being salient
- Background probability of a superpixel v_j is $\mathcal{P}_B(v_j)$

$$\mathcal{S}(v_i) = \sum_{j=1}^N d_f(v_i, v_j) \exp\left(-\frac{1}{2\sigma_1^2} \left(d_s(v_i, v_j)\right)^2\right)$$

Feature
distance

Inverse of spatial
distance

Background information

- Add semi-supervision
- Use background information
- For every superpixel, find its probability of belonging to background
 - i.e. not being salient
- Background probability of a superpixel v_j is $\mathcal{P}_B(v_j)$
- Modified saliency equation

$$\mathcal{S}(v_i) = \sum_{j=1}^N d_f(v_i, v_j) \exp\left(-\frac{1}{2\sigma_1^2} \left(d_s(v_i, v_j)\right)^2\right) \mathcal{P}_B(v_j)$$

Feature
distance

Inverse of spatial
distance

Background
probability

Background superpixels

- Boundary superpixels may belong to background

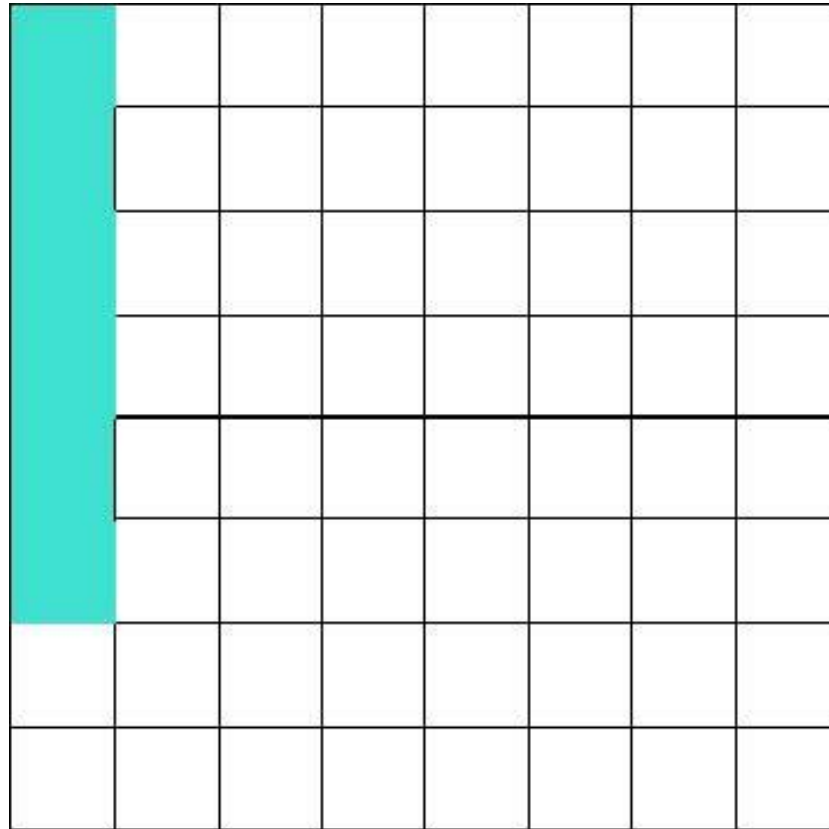


Image superpixel similarity. Same color indicates high feature similarity

Continued ...

- Non-boundary superpixel with high background probability

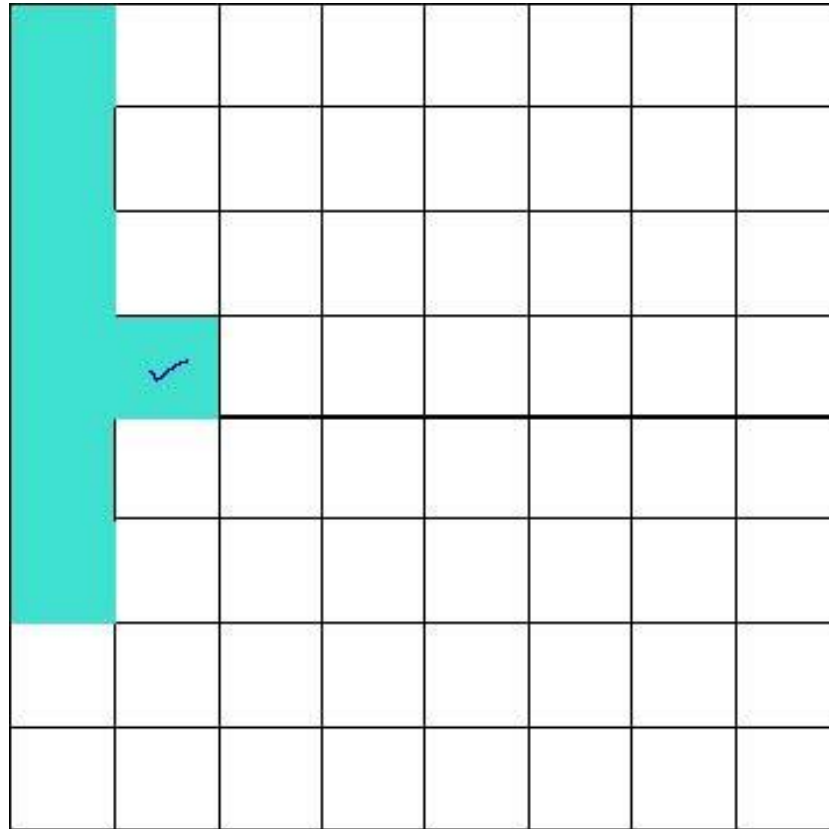


Image superpixel similarity. Same color indicates high feature similarity

Continued ...

- Boundary superpixel similar to non-boundary superpixels

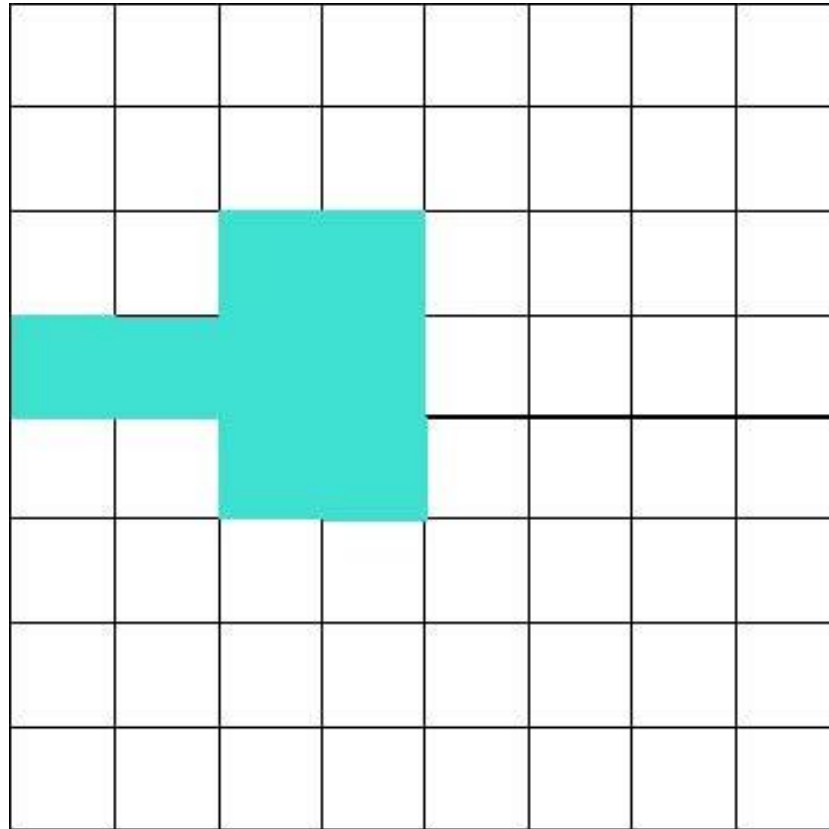


Image superpixel similarity. Same color indicates high feature similarity

Continued ...

- Boundary superpixel with small background probability

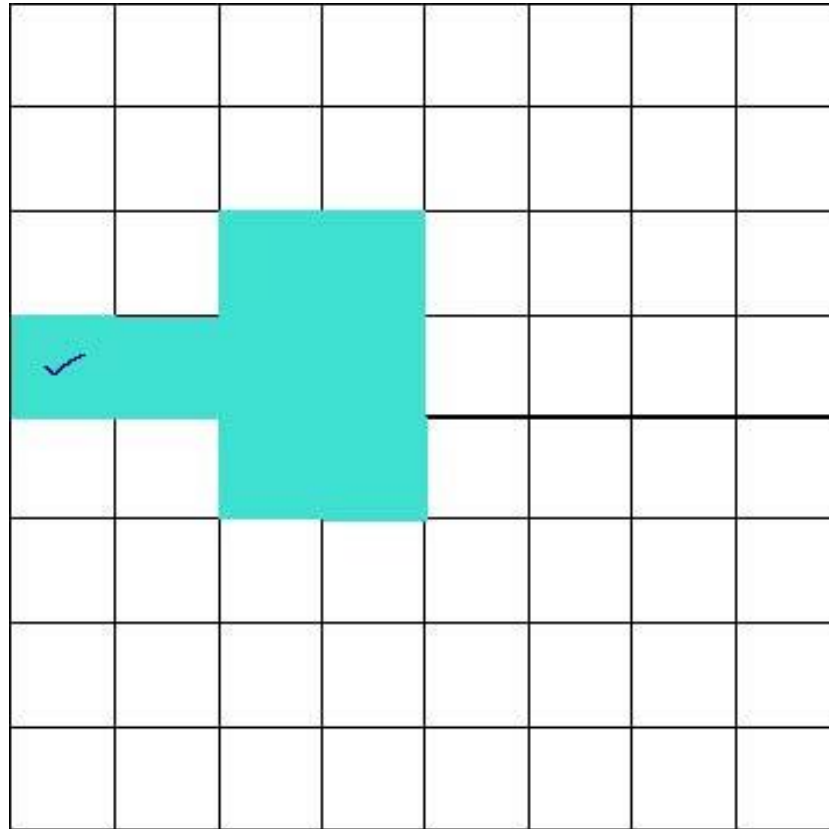


Image superpixel similarity. Same color indicates high feature similarity

Continued ...

- Introduce geodesic distance that combines
 - Feature distance
 - Spatial location

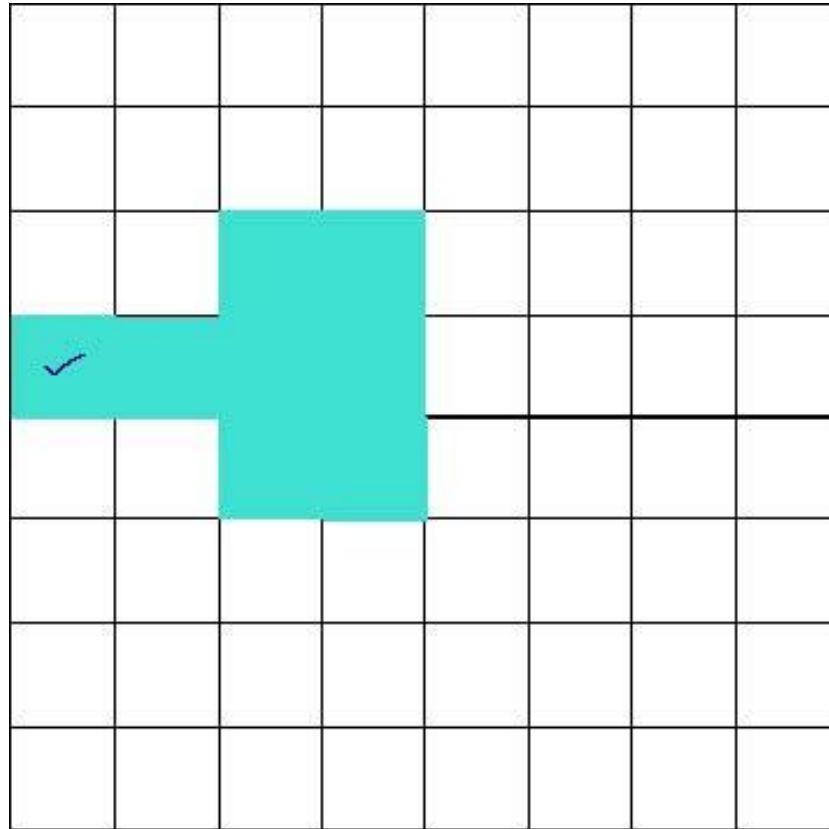


Image superpixel similarity. Same color indicates high feature similarity

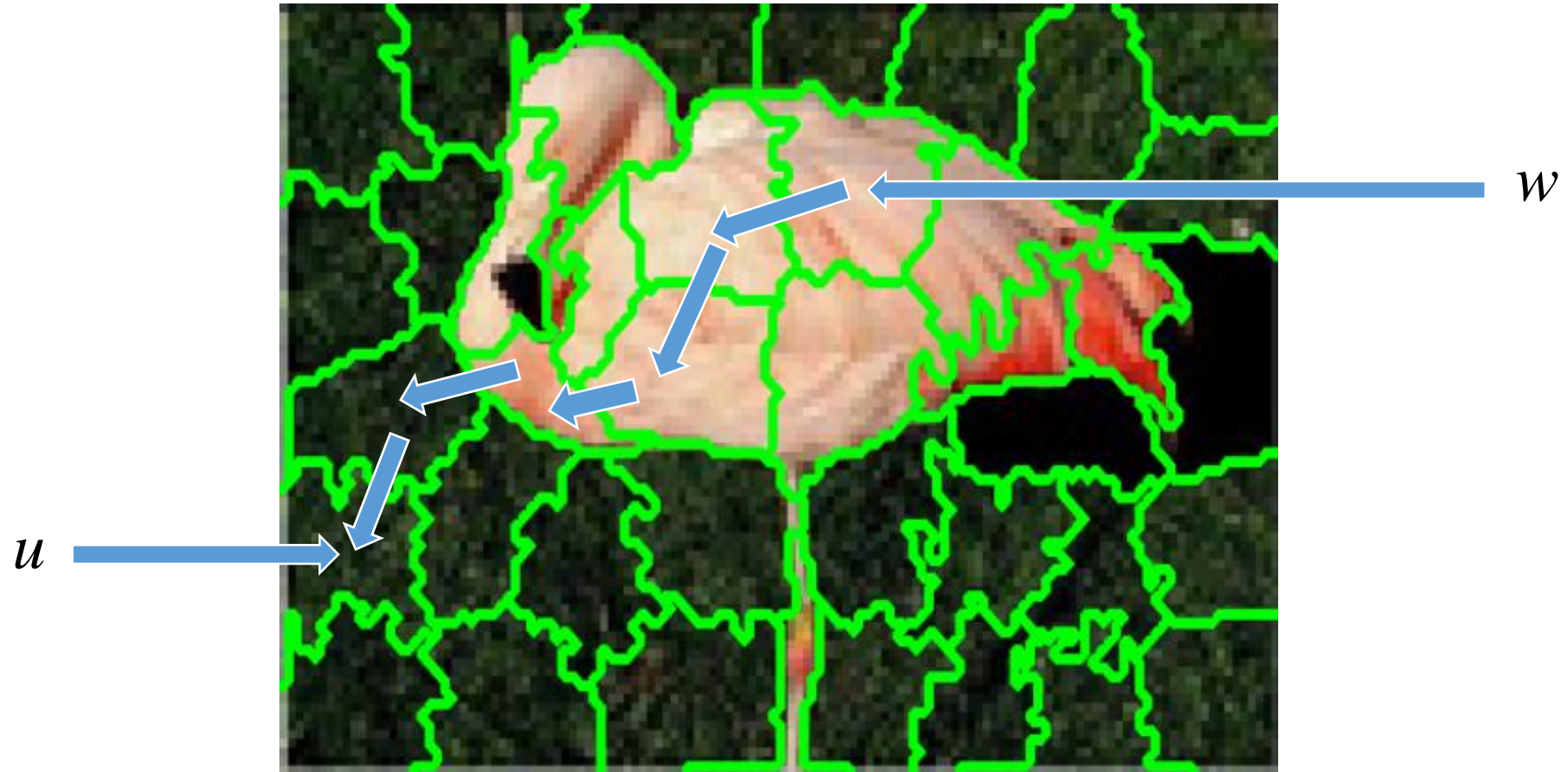
Geodesic distance



Geodesic distance



Geodesic distance



Geodesic distance

- Geodesic distance between two superpixels u and w is
 - the sum of feature distances of neighboring superpixels
 - along the *shortest path* $u = v_1, v_2, v_3, \dots, v_{L-1}, v_L = w$
 - between u and w in terms of feature distance

$$d_g(u, w) = \min_{\text{shortest path}} \sum_{i=1}^{L-1} d_f(v_i, v_{i+1})$$

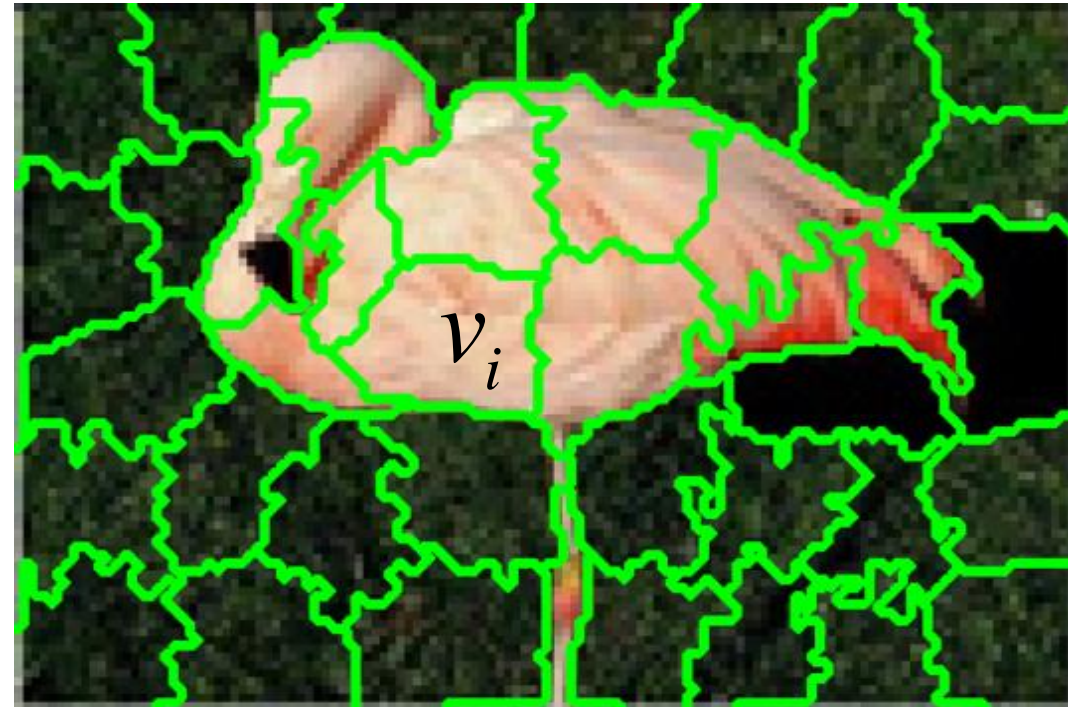
- L is different for different u and w

Background probability

- Geodesic similarity $d_g^*(v_i, v_j) = \exp\left(-\frac{1}{2\sigma_2^2} \left(d_g(v_i, v_j)\right)^2\right)$

Background probability

- Geodesic similarity $d_g^*(v_i, v_j) = \exp\left(-\frac{1}{2\sigma_2^2} \left(d_g(v_i, v_j)\right)^2\right)$
- Background contrast

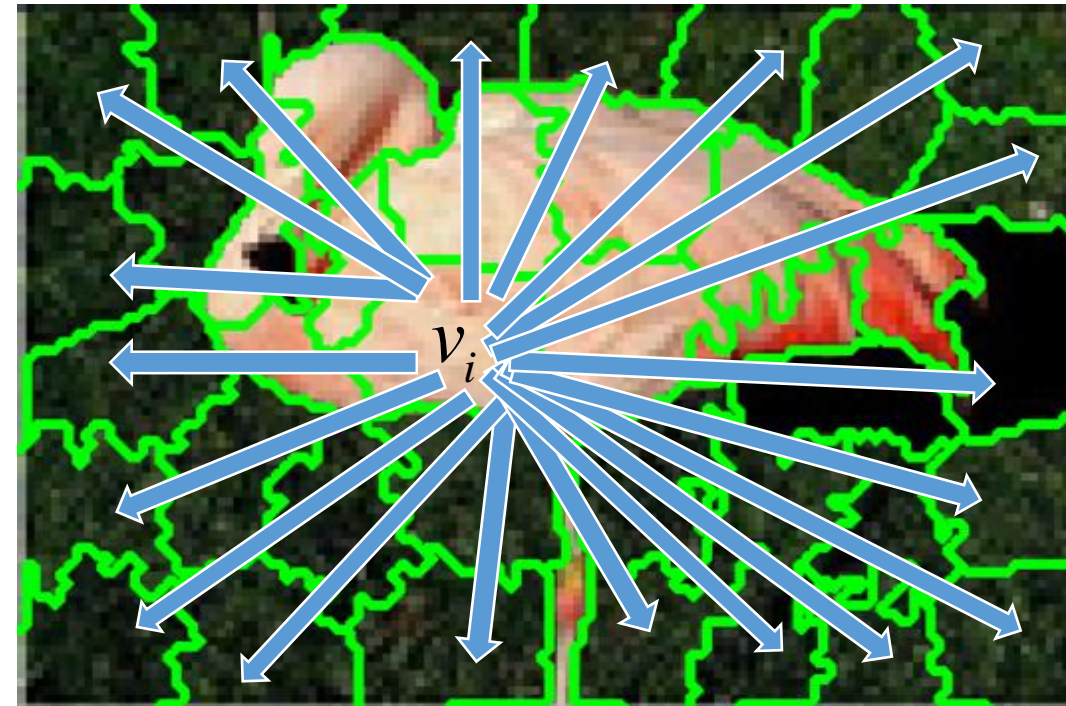


Background probability

- Geodesic similarity $d_g^*(v_i, v_j) = \exp\left(-\frac{1}{2\sigma_2^2} \left(d_g(v_i, v_j)\right)^2\right)$

- Background contrast

$$C_{\mathcal{B}}(v_i) = \frac{\sum_{j=1}^N d_g^*(v_i, v_j) \delta(v_j \in \mathcal{B})}{\sqrt{\sum_{j=1}^N d_g^*(v_i, v_j)}}$$



Background probability

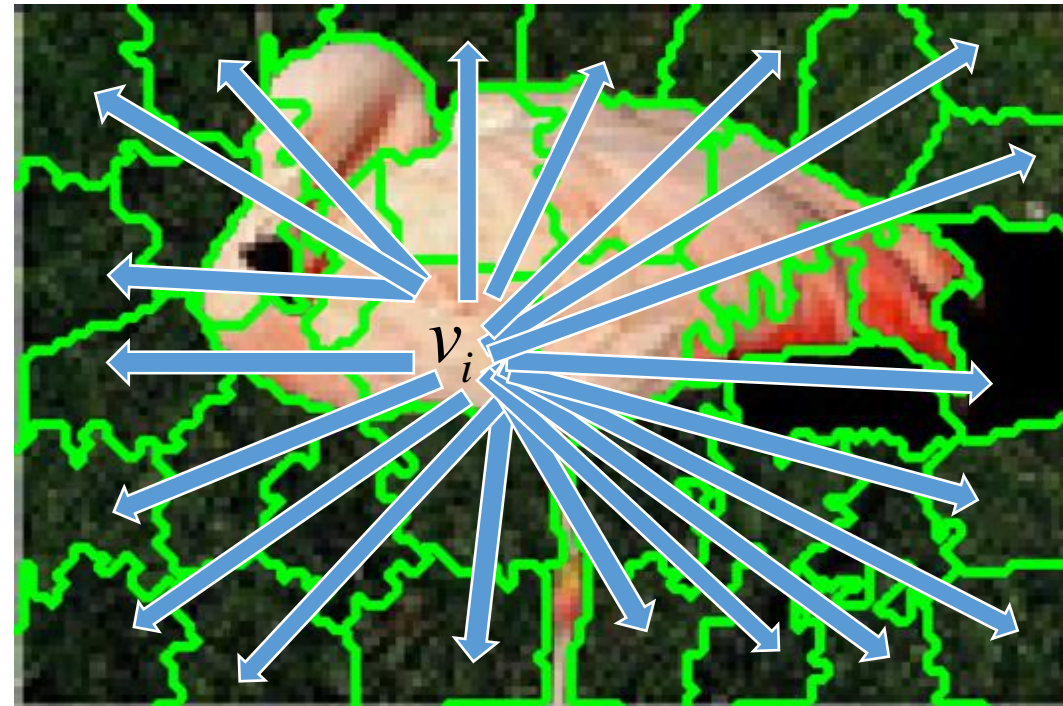
- Geodesic similarity $d_g^*(v_i, v_j) = \exp\left(-\frac{1}{2\sigma_2^2} \left(d_g(v_i, v_j)\right)^2\right)$

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$$C_B(v_i) = \frac{\sum_{j=1}^N d_g^*(v_i, v_j) \delta(v_j \in \mathcal{B})}{\sqrt{\sum_{j=1}^N d_g^*(v_i, v_j)}}$$

- Background probability of a superpixel

$$\mathcal{P}_B(v_i) = 1 - \exp\left(-\frac{1}{2\sigma_3^2} \left(C_B(v_i)\right)^2\right)$$



Saliency equation re-visited

- Saliency value of a superpixel v_i

$$\mathcal{S}(v_i) = \sum_{j=1}^N d_f(v_i, v_j)$$

$$\mathcal{S}(v_i) = \sum_{j=1}^N d_f(v_i, v_j) \exp\left(-\frac{1}{2\sigma_1^2} \left(d_s(v_i, v_j)\right)^2\right)$$

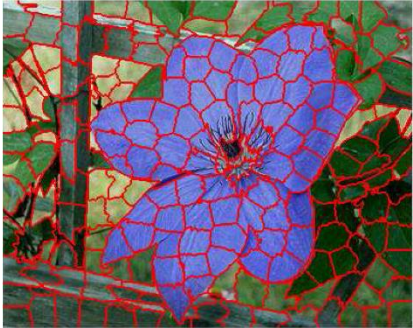
$$\mathcal{S}(v_i) = \sum_{j=1}^N d_f(v_i, v_j) \exp\left(-\frac{1}{2\sigma_1^2} \left(d_s(v_i, v_j)\right)^2\right) \mathcal{P}_B(v_j)$$

Feature
distance

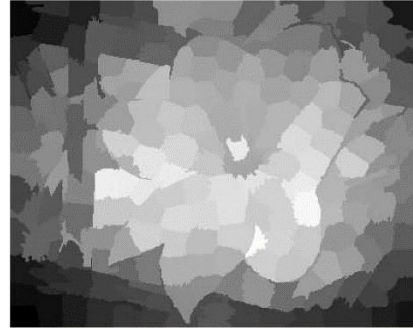
Inverse of spatial
distance

Background
probability

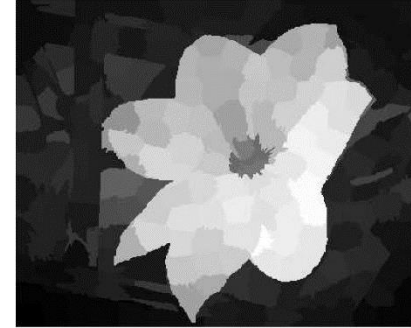
Results



Input image



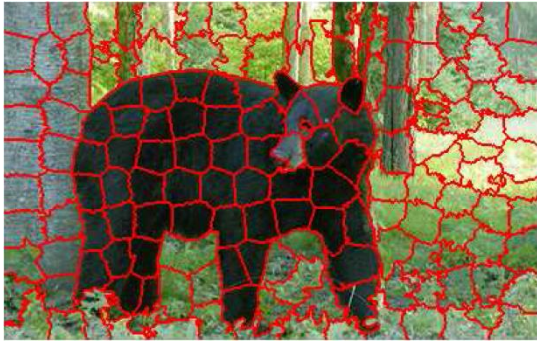
Saliency map
with
Feature distance
+
Inverse of
spatial distance



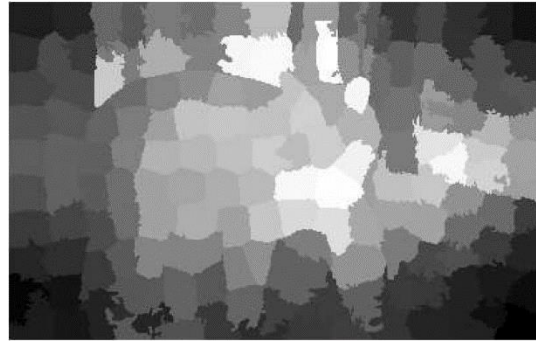
Saliency map
with
Feature distance
+
Inverse of
spatial distance
+
Background
probability

Result from Zhu *et al.*, CVPR 2014

Results



Input image



Saliency map
with
Feature distance
+
Inverse of
spatial distance

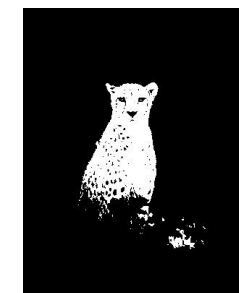
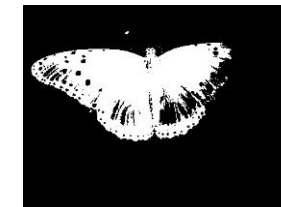
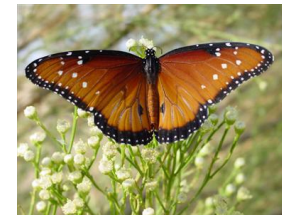


Saliency map
with
Feature distance
+
Inverse of
spatial distance
+
Background
probability

Result from Zhu *et al.*, CVPR 2014

Challenges

- Local approach (center-surround window)
 - Pixel based
 - Boundary of large smooth salient object detected
- Global approach (global comparison)
 - Superpixel based and patch based
 - Salient objects are not uniformly highlighted
 - Upon thresholding,
 - textures, holes, spurious points, incomplete objects
- Frequency domain
 - Saliency map is blurred



Input image

Thresholded
saliency

Result from Perazzi *et al.*, CVPR 2012

Image courtesy: MSRA dataset

Saliency in synthetic data

- Use local approach (center-surround window)

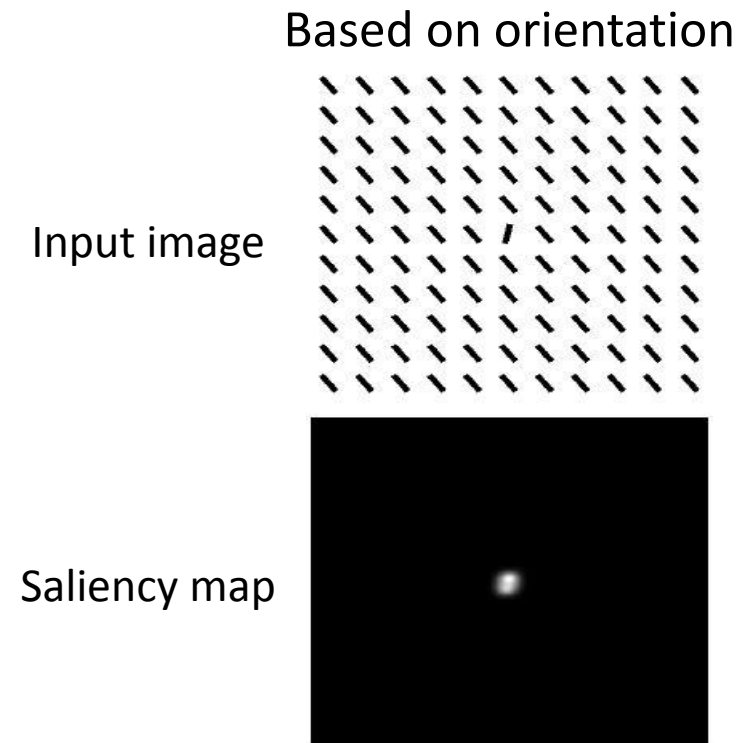
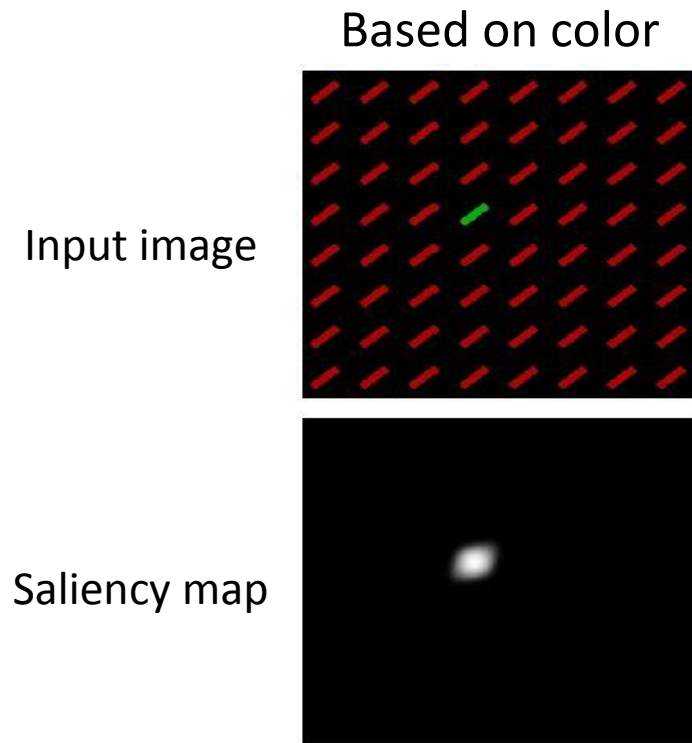
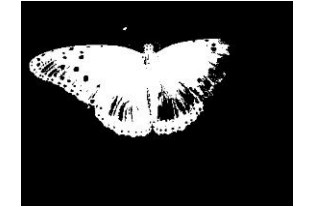


Image courtesy: Gao *et al.*

Challenges

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Input image

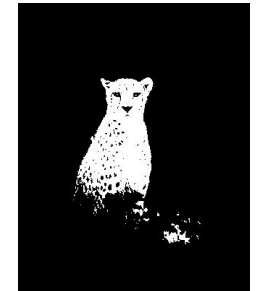
Thresholded
saliency

Result from Perazzi *et al.*, CVPR 2012

Image courtesy: MSRA dataset

Challenges

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Input image

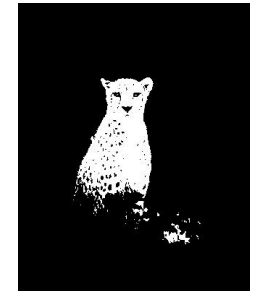
Thresholded
saliency

Result from Perazzi *et al.*, CVPR 2012

Image courtesy: MSRA dataset

Challenges

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 - Upon thresholding,
 - **textures, holes, spurious points, incomplete objects**
 - **possible solution1: neighboring superpixels – similar saliency value**
- Frequency domain
 - Saliency map is blurred



Input image

Thresholded
saliency

Result from Perazzi *et al.*, CVPR 2012

Image courtesy: MSRA dataset

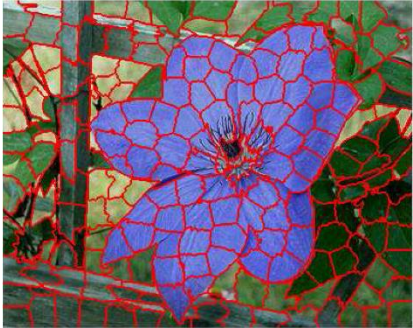
Saliency optimization

- Minimize the cost function

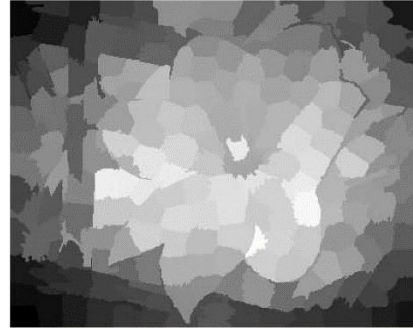
$$\min_s \left(\left(\sum_{i=1}^N \sum_{\substack{j=1 \\ j \neq i}}^N (s_i - s_j)^2 d_f(v_i, v_j) \right) + \left(\sum_{i=1}^N (1 - s_i)^2 \mathcal{S}(v_i) \right) + \left(\sum_{i=1}^N (s_i)^2 \mathcal{P}_B(v_i) \right) \right)$$

- s_i is the updated saliency value of superpixel v_i after optimization
- First term: data fitting term
- Second term: foreground (salient region) prior
- Third term: background (non-salient region) prior

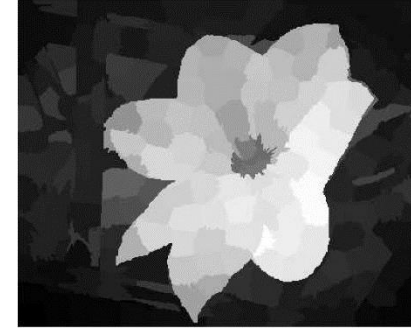
Results



Input image



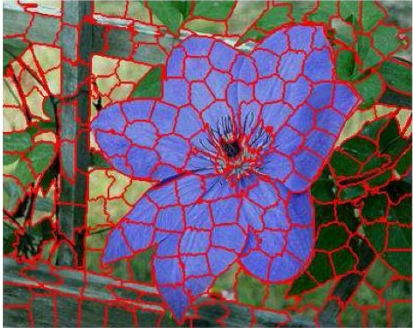
Saliency map
with
Feature distance
+
Inverse of
spatial distance



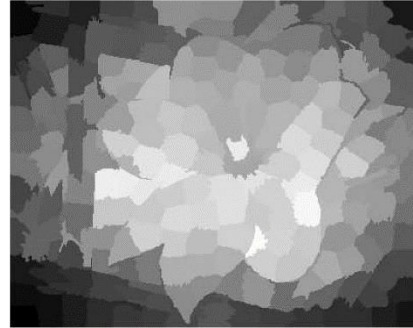
Saliency map
with
Feature distance
+
Inverse of
spatial distance
+
Background
probability

Result from Zhu *et al.*, CVPR 2014

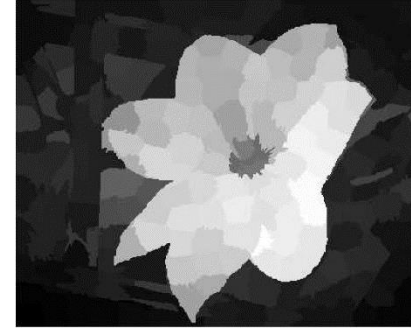
Results



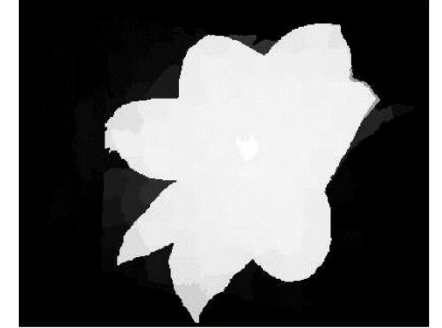
Input image



Saliency map
with
Feature distance
+
Inverse of
spatial distance



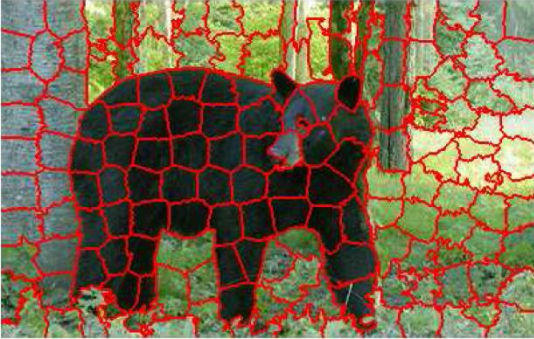
Saliency map
with
Feature distance
+
Inverse of
spatial distance
+
Background
probability



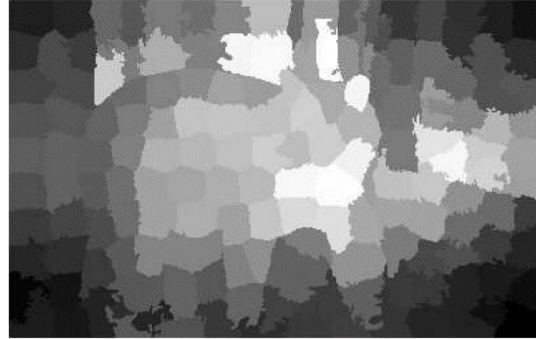
Saliency map
after
optimization

Result from Zhu *et al.*, CVPR 2014

Results



Input image



Saliency map
with
Feature distance
+
Inverse of
spatial distance



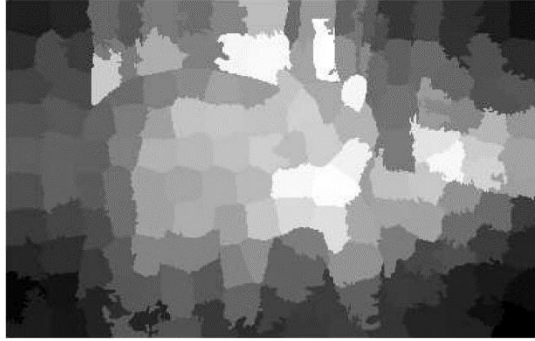
Saliency map
with
Feature distance
+
Inverse of
spatial distance
+
Background
probability

Result from Zhu *et al.*, CVPR 2014

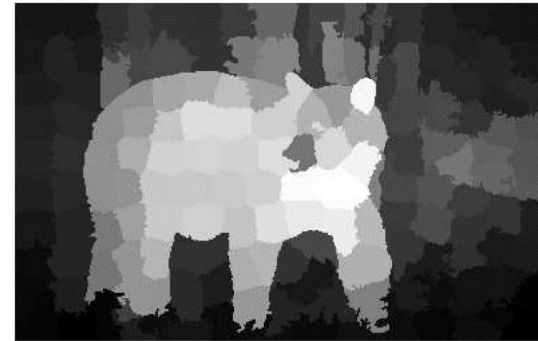
Results



Input image



Saliency map
with
Feature distance
+
Inverse of
spatial distance



Saliency map
with
Feature distance
+
Inverse of
spatial distance
+
Background
probability

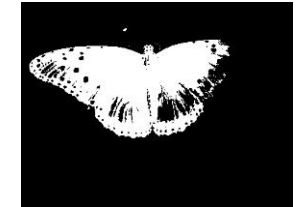


Saliency map
after
optimization

Result from Zhu *et al.*, CVPR 2014

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 - Pixel based
 - Boundary of large smooth salient object detected
- Global approach (global comparison)
 - Superpixel based and patch based
 - Salient objects are not uniformly highlighted
 - Upon thresholding,
 - **textures, holes, spurious points, incomplete objects**
- Frequency domain
 - Saliency map is blurred



Input image

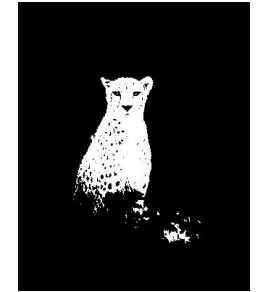
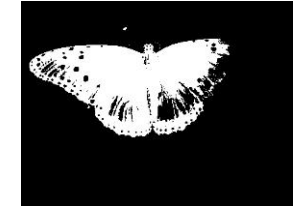
Thresholded
saliency

Result from Perazzi *et al.*, CVPR 2012

Image courtesy: MSRA dataset

Challenges

- Local approach (center-surround window)
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 - Boundary of large smooth salient object detected
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 - Superpixel based and patch based
 - Salient objects are not uniformly highlighted
 - Upon thresholding,
 - **textures, holes, spurious points, incomplete objects**
 - **possible solution2: obtain larger regions before saliency computation**
- Frequency domain
 - Saliency map is blurred



Input image

Thresholded
saliency

Result from Perazzi *et al.*, CVPR 2012

Image courtesy: MSRA dataset

Thank You