Learning to Detect A Salient Object

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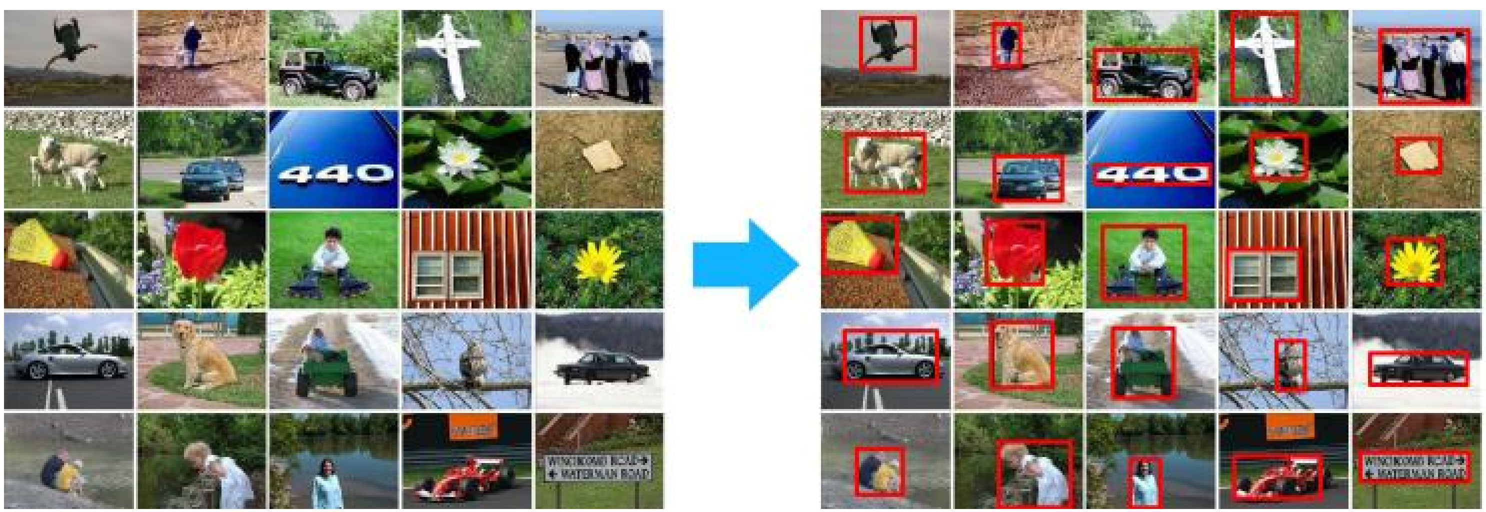
Outline

- Introduction
- Image Database
- Salient Object Detection
  - CRF Learning
  - Salient Object Features
- Evaluation
- Discussion and Conclusion

Introduction

- Study visual attention by detecting a salient object in an input image.
- People naturally pay more attention to salient objects.
  - A person, a face, a car, an animal, a road sign, etc.
- Formulate salient object detection as image segmentation problem.
  - Separate the salient object from the image background.

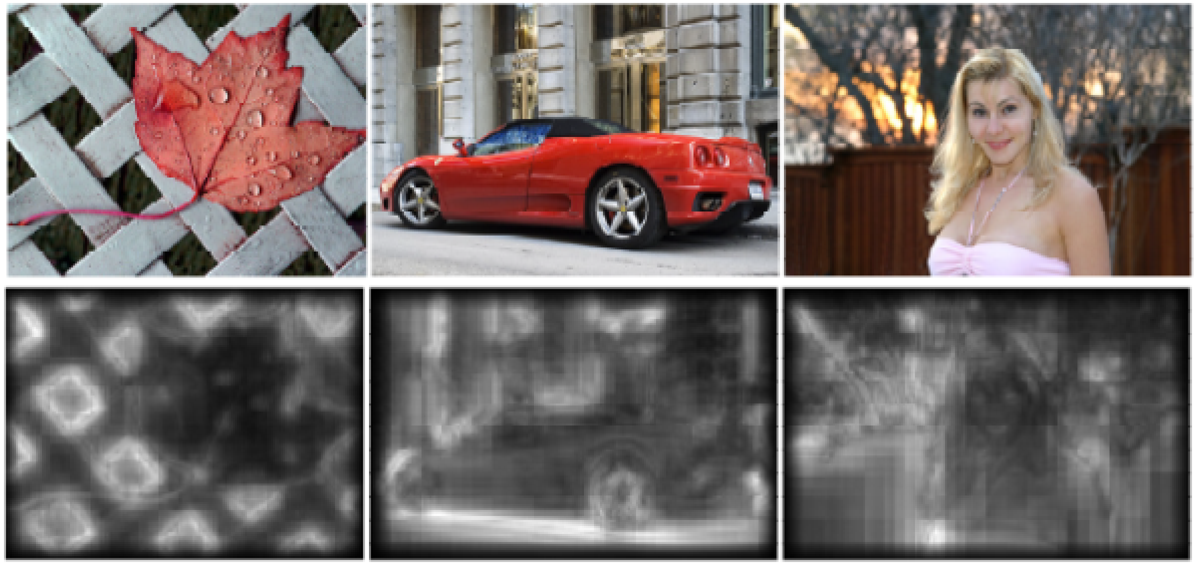


Introduction

- Applications for visual attention
  - Automatic image cropping, adaptive image display, image/video compression, advertising design, etc.
- Existing visual attention approaches
  - Bottom-up computational framework

Introduction

- Difficulty
  - Although existing approaches work well in finding a few fixation locations, they are not able to accurately detect where visual attention should be.



Introduction

- Contributions
  - The first large image database available for quantitative evaluation
  - High-level concept of salient object for visual attention computation
  - CRF learning framework with a set of novel local, regional, and global features to define a generic salient object

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Image Database

- Different people have different ideas about what a salient object in an image is.
  - Voting strategy by multiple users.

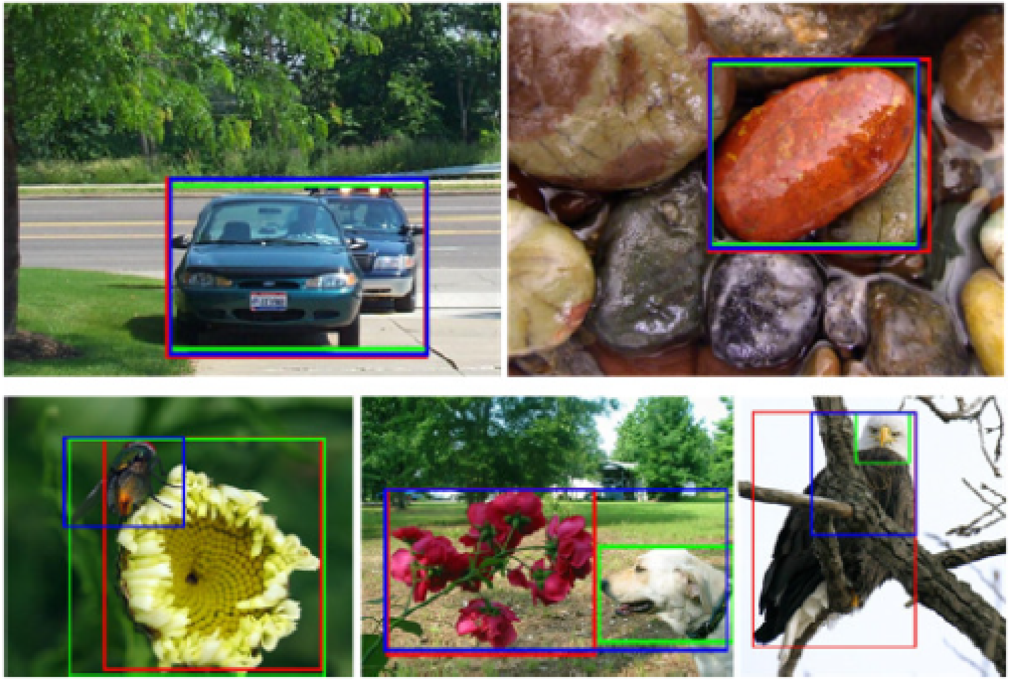

Image Database

- Salient object representation
  - A binary mask

$$A = \{a_x\}\ ,\ \text{for each pixel } x,\ a_x \in \{1, 0\}$$

- Image source
  - 130,099 high quality images from a variety of sources
  - 60,000+ images with a salient object or a distinctive foreground object
  - 20,840 images for labeling
- Two-stage labeling process
  - Ask the user to draw a rectangle which encloses the most salient object in the image.
  - Reduce labeling inconsistency with voting.

Image Database

- The first stage
  - 3 users label all 20,840 images.
  - Saliency probability map

$$g_x = \frac{1}{M}\sum_{m=1}^{M} a_x^m$$

M: the number of users

$A^m = \{a_x^m\}$: the binary mask labeled by the mth user

  - Image set ***A***
  - Labeling consistency

$$C_t = \frac{\sum_{x \in \{g_x > t\}} g_x}{\sum_x g_x}$$

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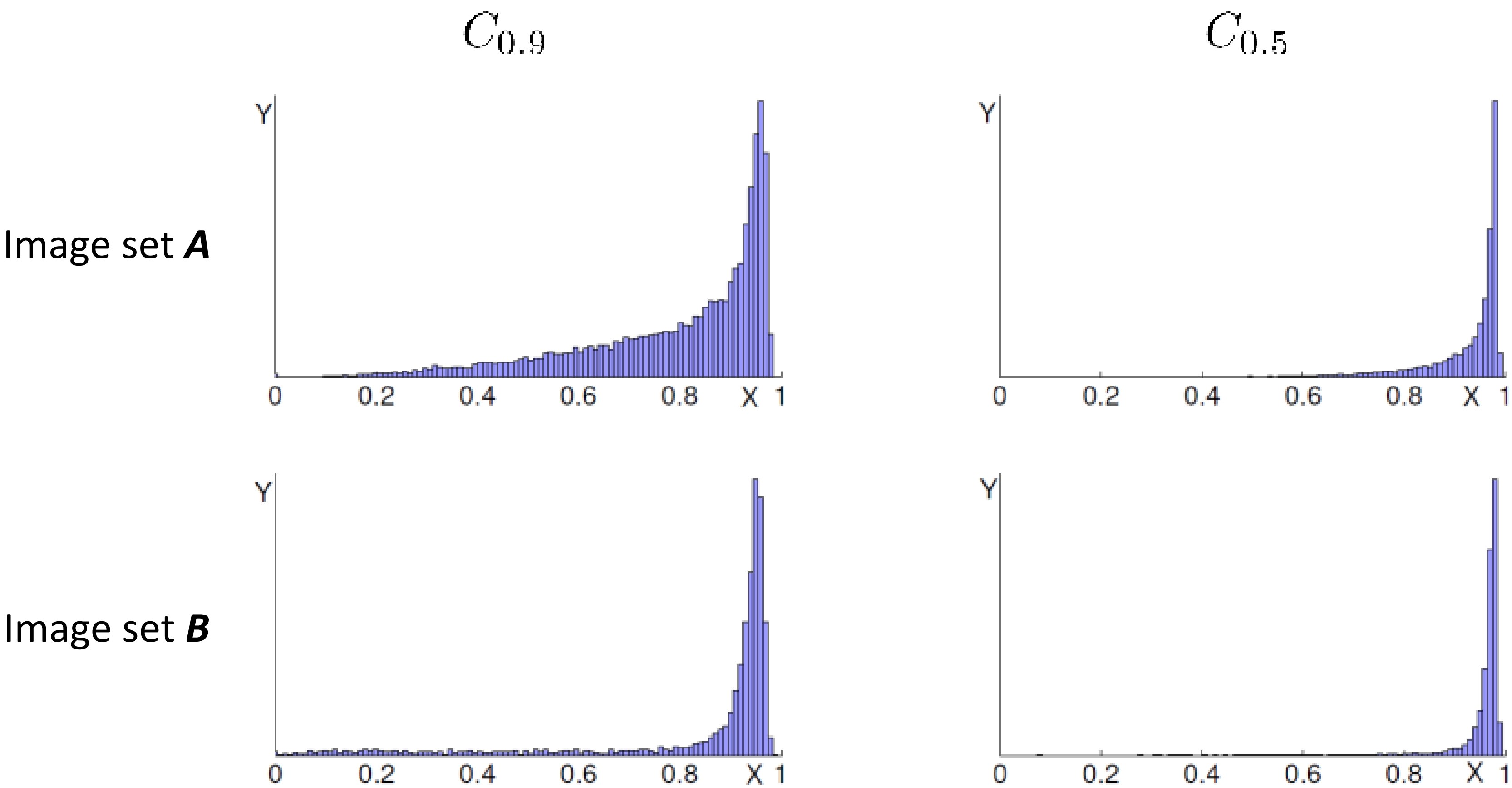
Image Database

- The second stage
  - Randomly selected 5000 highly consistent images from the image set ***A*** (i.e., $C_{0.9} > 0.8$)
  - 9 users label the salient object rectangle.
  - Image set ***B***
- After the two-stage labeling process, the salient object is defined based on the majority agreement of users and represented as a saliency probability map.

Image Database



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Salient Object Detection

- Formulated as binary labeling problem
- Conditional Random Field (CRF) framework
  - The probability of the label $A = \{a_x\}$ given the image I is modeled as a conditional distribution:

$$P(A|I) = \frac{1}{Z} e^{-E(A|I)}$$

$$E(A|I) = \sum_x \sum_{k=1}^{K} \lambda_k F_k(a_x, I) + \sum_{x,x'} S(a_x, a_{x'}, I)$$

Salient Object Detection

- Conditional Random Field (CRF) framework
  - Get an optimal linear combination of features by estimating the linear weights under the Maximized Likelihood (ML) criteria:

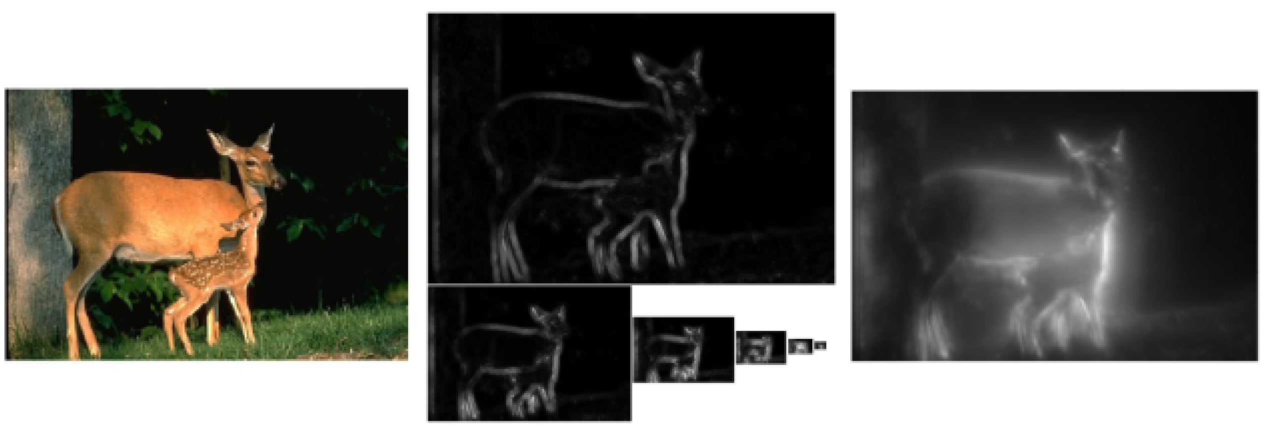
$$\overrightarrow{\lambda}^* = \arg\max_{\overrightarrow{\lambda}} \sum_n \log P(A^n | I^n; \overrightarrow{\lambda}), \overrightarrow{\lambda} = \{\lambda_k\}_{k=1}^K$$

  - Advantages over Markov Random Field (MRF)
    - Arbitrary low-level or high-level features can be used.
    - Provide an elegant framework to combine multiple features with effective learning.

Salient Object Features

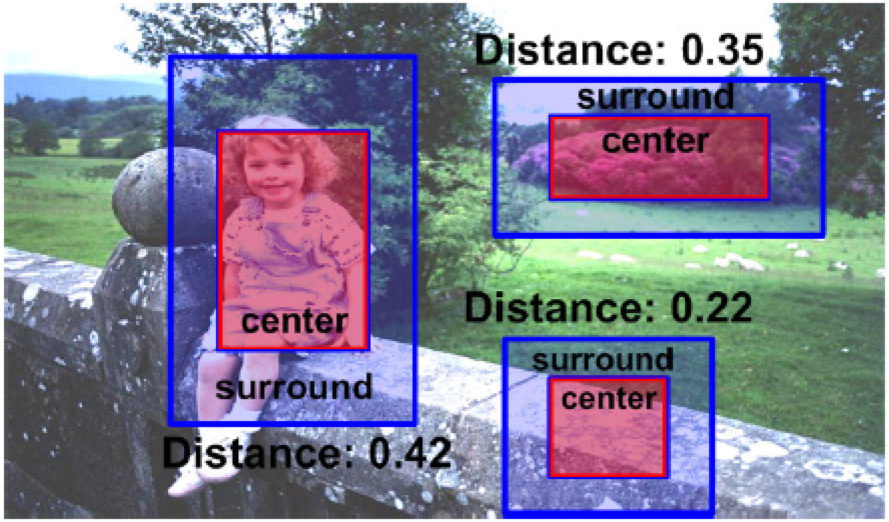
- Multi-scale contrast
  - Contrast is the most commonly used local feature because the contrast operator simulates the human visual receptive fields.
  - A linear combination of contrasts in the Gaussian image pyramid:

$$f_c(x, I) = \sum_{l=1}^{L} \sum_{x' \in N(x)} \|I^l(x) - I^l(x')\|^2$$



Salient Object Features

- Center-surround histogram
  - Salient objects usually have a larger extent than local contrast and can be distinguished from its surrounding context.
  - Measure how distinct the salient object is with respect to its surrounding area, using the distance between color histograms.



Salient Object Features

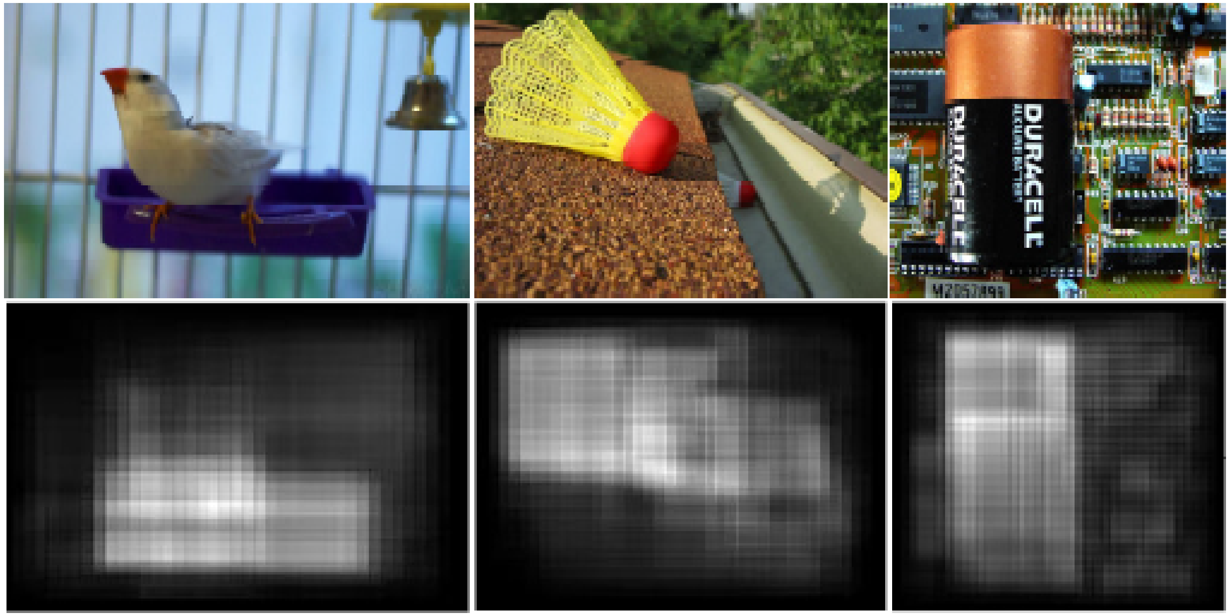
- Center-surround histogram
  - Sum of spatially weighted distances:

Salient Object Features

- Center-surround histogram

Non-rectangular shape of salient object?

Other visual cues?



Salient Object Features

- Color spatial distribution
  - The wider a color is distributed in the image, the less possible a salient object contains this color.
  - Spatial variance of color, horizontal and vertical:

$$p(c|I_x) = \frac{w_c \mathcal{N}(I_x|\mu_c, \Sigma_c)}{\sum_c w_c \mathcal{N}(I_x|\mu_c, \Sigma_c)}, \mathcal{N} : \text{Gaussian Mixture Model}$$

Salient Object Features

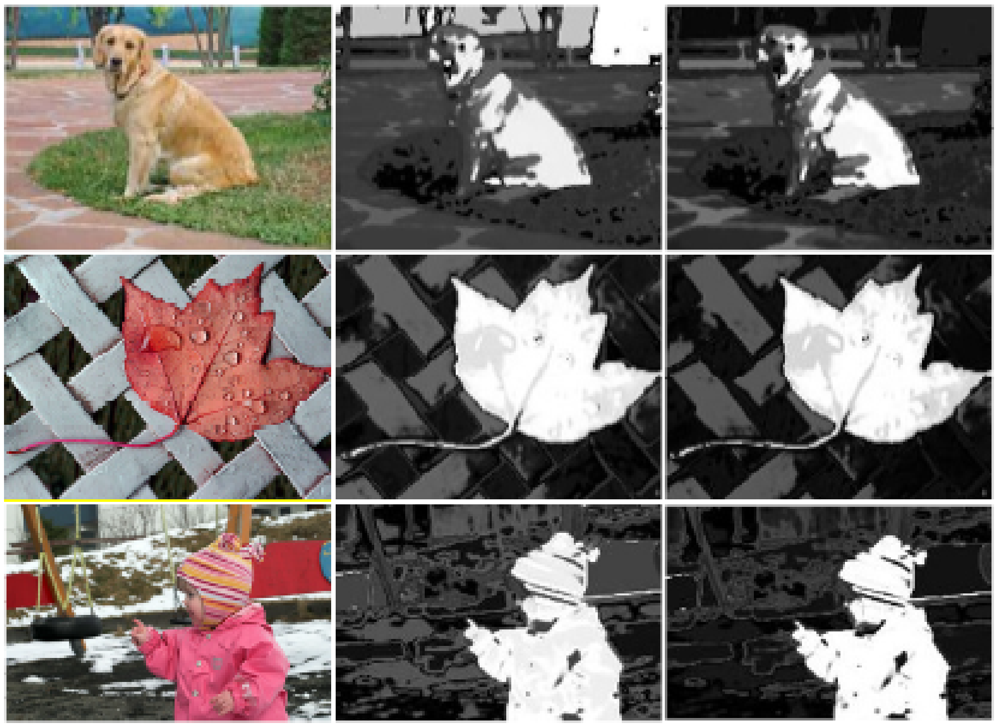
- Color spatial distribution
  - The spatial variance of color at image corners or boundaries may also be small because the image is cropped from the whole scene.
  - Center-weighted, spatial-variance color feature:

$$f_s(x, I) \propto \sum_c p(c|I_x)(1 - V(c))(1 - D(c))$$

Salient Object Features

- Color spatial distribution

Non-centered salient object?



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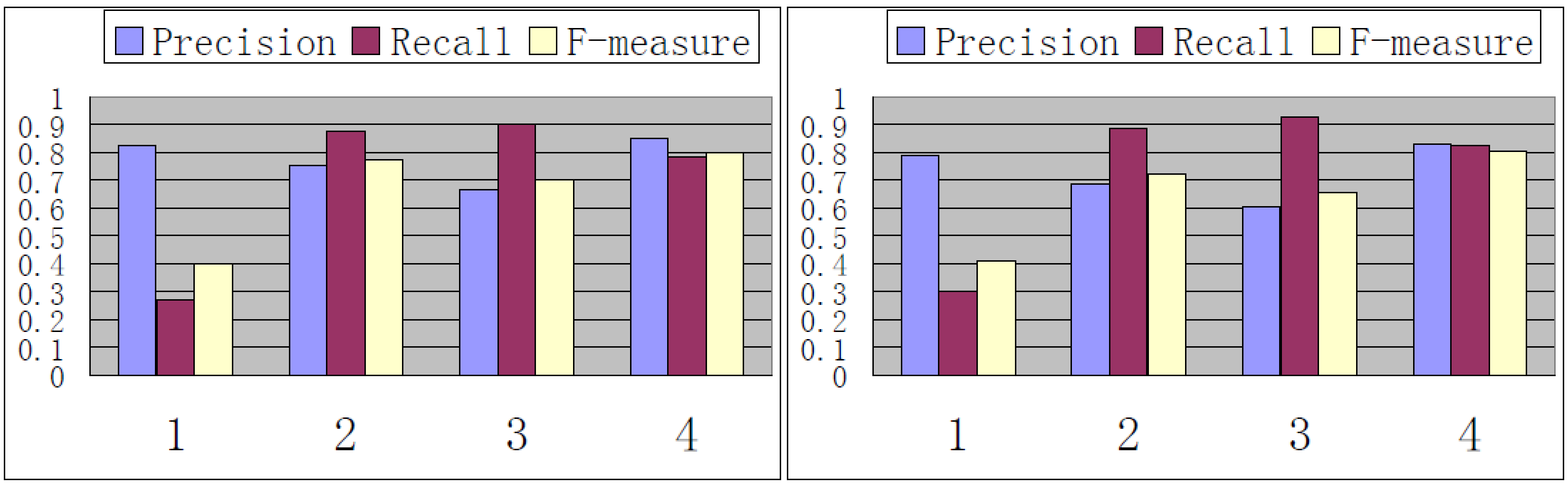
Evaluation

- Effectiveness of features and CRF learning

1. multi-scale contrast, 2. center-surround histogram, 3. color spatial distribution, 4. combination



(a) image set $\mathcal{A}$ (b) image set $\mathcal{B}$

$$\text{Precision} = \frac{\sum_x g_x a_x}{\sum_x a_x}, \text{Recall} = \frac{\sum_x g_x a_x}{\sum_x g_x}, \text{F-measure} = \frac{(1+\alpha) \times \text{Precision} \times \text{Recall}}{\alpha \times \text{Precision} + \text{Recall}}$$

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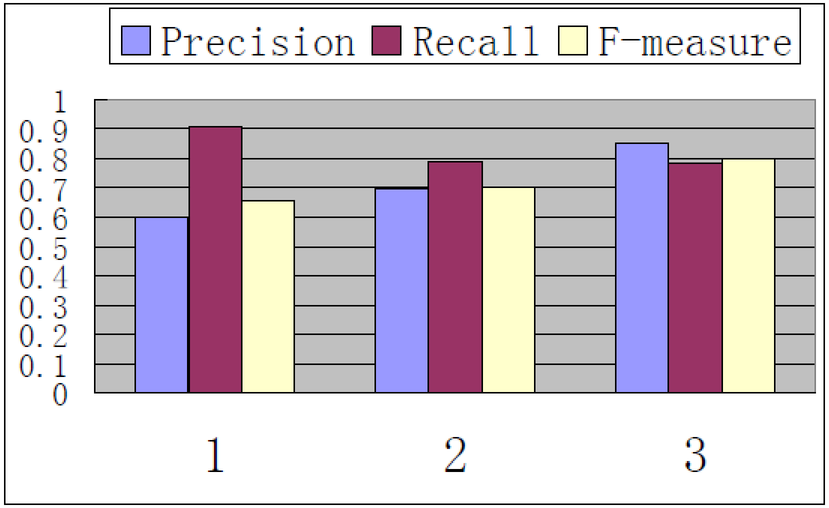
Evaluation

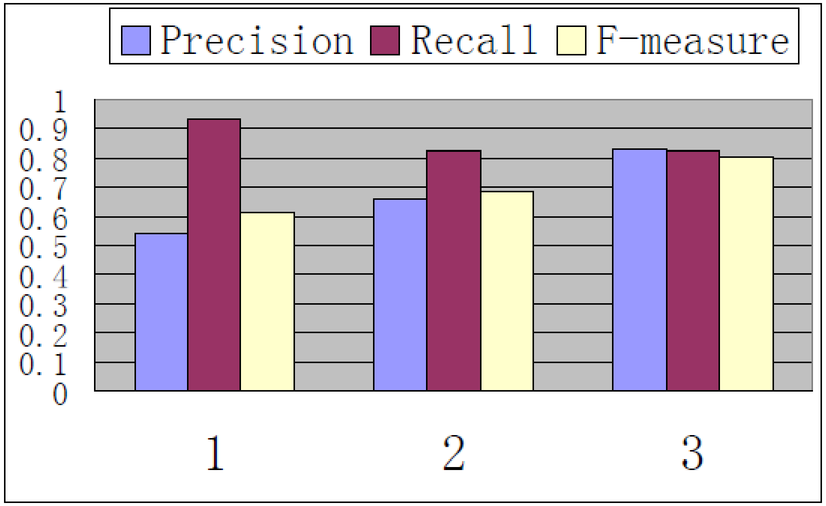
- Effectiveness of features and CRF learning

Contribution of contrast?

Evaluation

- Comparison with other approaches
  - Recall rate is not much of a useful measure in visual attention.

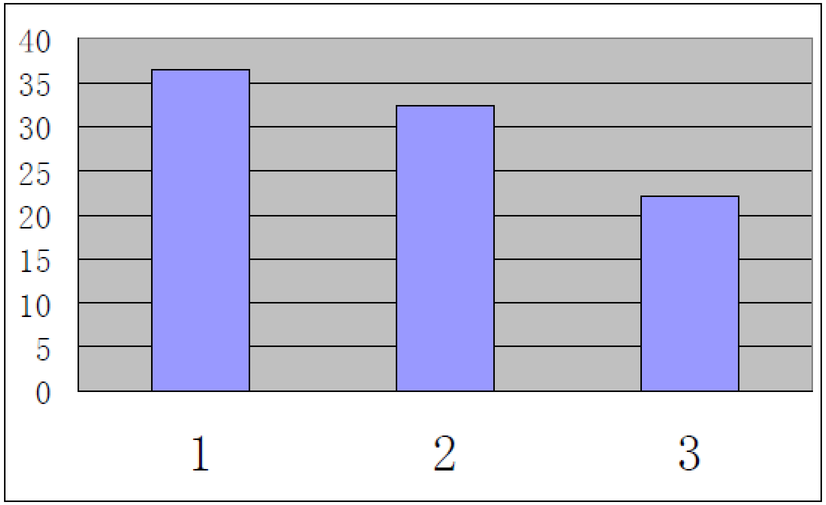




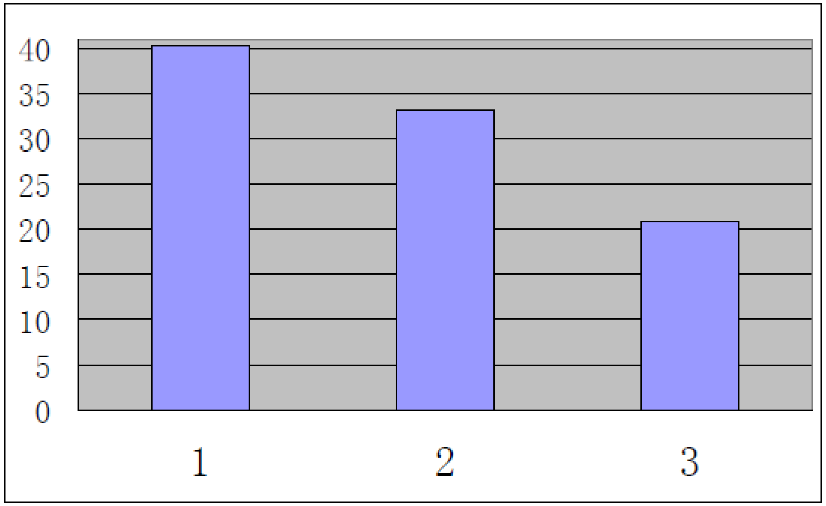
(a) preci./recall, image set $\mathcal{A}$ (b) preci./recall, image set $\mathcal{B}$

Evaluation

- Comparison with other approaches
  - Recall rate is not much of a useful measure in visual attention.



(c) BDE, image set $\mathcal{A}$

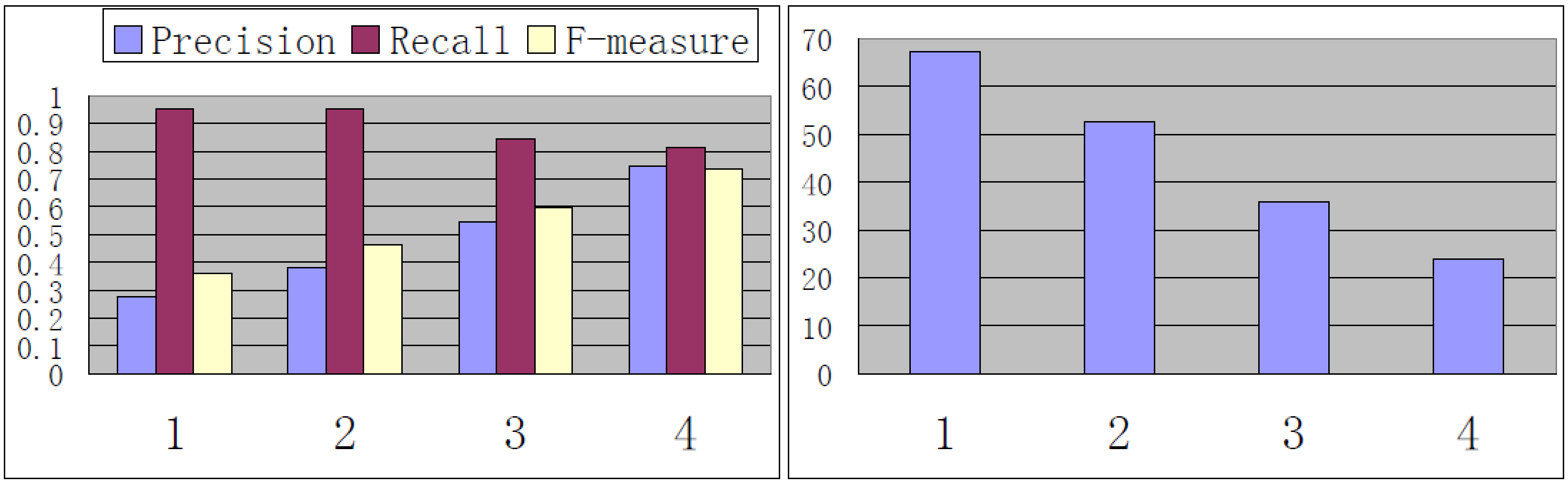


(d) BDE, image set $\mathcal{B}$

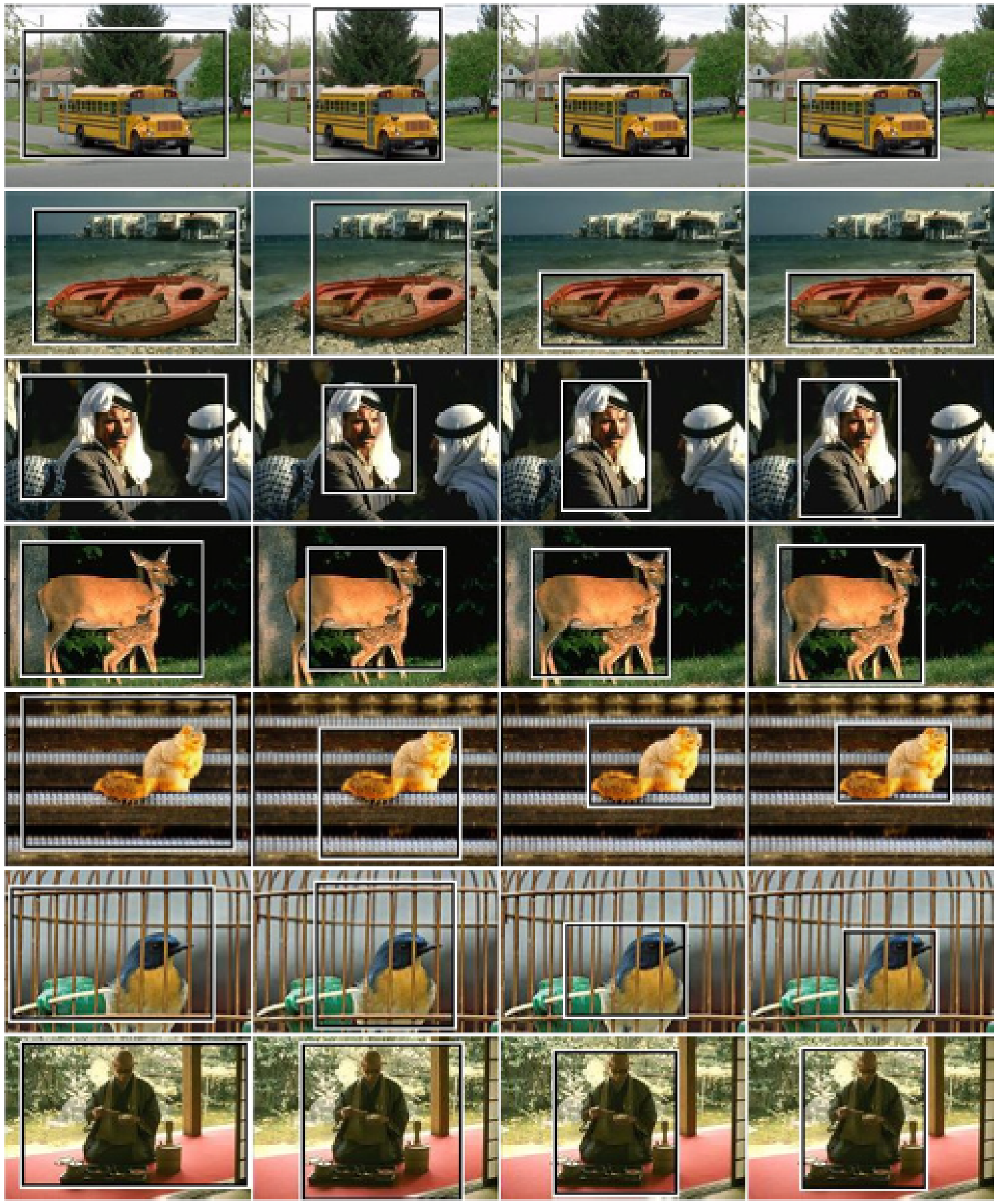
BDE: boundary displacement error

Evaluation

- Comparison with other approaches
  - The real challenge: high precision on small salient objects
    - Object/image ratio in the range [0 , 0.25]



(a) preci./recall (b) BDE



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Discussion and Conclusion

- Present a supervised approach for salient object detection formulated as an image segmentation problem using a set of local, regional, and global salient object features.
- Salient object detection has wider applications.
  - Content-based image retrieval
  - Automatic collecting and labeling of image data
- Future work
  - Non-rectangular shapes of salient objects
  - Non-linear combination of features
  - More sophisticated visual features
  - Multiple salient object detection

Discussion and Conclusion

- Multiple salient object detection

Discussion and Conclusion

- Failure cases and challenges
  - Hierarchical salient object detection

Thank You!