What Makes a Patch Distinct?

Image Processing Presentation

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Outline

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1. Introduction
2. Proposed Approach
   - Pattern Distinctness
   - Color Distinctness
   - Putting it all together
3. Performance Evaluation
4. Conclusion

- What is patch?
  - Group of pixels
- What are distinct patches?
  - Most important (target) object
- Application
  - Object detection and recognition
  - Image compression

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Distinct patches

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- Detect distinct Colors
- Detect distinct Patterns

Distinct patches (only color)

- Detect distinct Colors
- Detect distinct Patterns

Distinct patches (only pattern)

- Analysis of the inner statistics of patches
- Principal Component Analysis (PCA)

Distinct patches (color + pattern)

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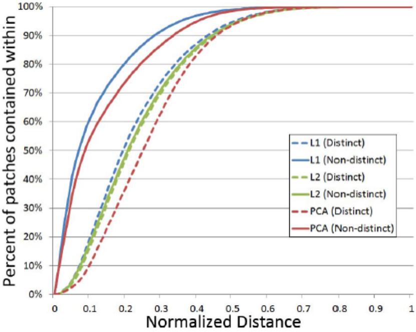
Pattern Distinctness

Analyzing the properties of patches of natural images, they make several observations that improve detection accuracy via a fast and simple solution

Pattern Distinctness

First Observation

- First observation
  - Non-distinct patches mostly concentrated around average patch
  - Distinct patches are more scattered
  - L1 and PCA approaches (why???)



Scatter distinguishes between distinct and non-distinct patches

Pattern Distinctness

First Observation

- Distinct patches can be identified by measuring the distance to the average patch P_A

$$P_A = \frac{1}{N} \sum_{x=1}^{N} p_x \tag{1}$$

  Image patch p_x is considered distinct if it is dissimilar to the average patch P_A
- Computing the distance between every patch and the average patch (not accurate)

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Pattern Distinctness
Second Observation

- Second observation:
  - Distance to the average patch should consider the patch distribution in the image
- Computing the distance along the principal components

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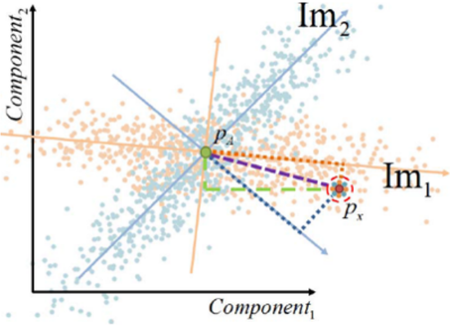

Saliency should depend on patch distribution

Pattern Distinctness

Second Observation

- Mathematically, this boils down to calculating the L_1 norm of p_x in PCA coordinates
- Pattern distinctness is defined by:

$$P(p_x) = \|\tilde{p_x}\|_1 \tag{2}$$

  where $\tilde{p_x}$ is p_x's coordinates in PCA system
- Patch is distinct if the path connecting it to the average patch, along the principal components, is long.

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Color Distinctness

Two Steps

Color distinctness

- First, segment the image into regions
  - Simple Linear Iterative Clustering (SLIC) algorithm superpixels
- Second, determine which regions are distinct in color

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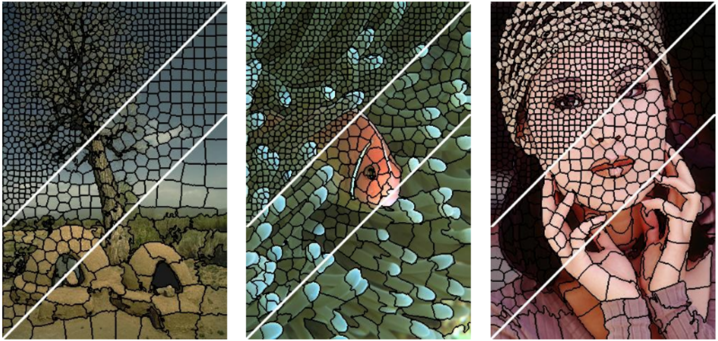
Color Distinctness

First Step



Segmented regions by SLIC [1]

[1] Credited to "SLIC Superpixels"

Color Distinctness

Second Step

- Given M regions, the color distinctness of region, p_x , is computed by:

$$C(p_x) = \sum_{x=1}^{M} \|p_x - p_i\|_2 \tag{3}$$

- This calculation is efficient due to small number of SLIC regions in most images

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- Multiply and normalize to the range $[0, 1]$

$$D(p_x) = P(p_x) \cdot C(p_x) \tag{4}$$

when $P(p_x)$ and $C(p_x)$ are Pattern and Color Distinctness, respectively

- It is not perfect, because two known priors on image organization need to be considered

Putting it all together
First Proposal

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when $P(p_x)$ and $C(p_x)$ are Pattern and Color Distinctness, respectively

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Putting it all together

Two known priors

First, salient pixels tend to be grouped together into clusters

Second, the subject of the photograph is near the center of the image

Putting it all together

Refinement

- Implementation in five steps:

STEP 1

Detect clusters of distinct pixels with different thresholds

STEP 2

Compute Center-of-mass of each thresholds

STEP 3

Place Gaussian
$\sigma = 10000$
at Center-of-mass

STEP 4

Add Gaussian
$\sigma = 5$
at center of image

STEP 5

Generate weight map
$G(p_x)$
sum all Gaussians

Putting it all together

Final Saliency

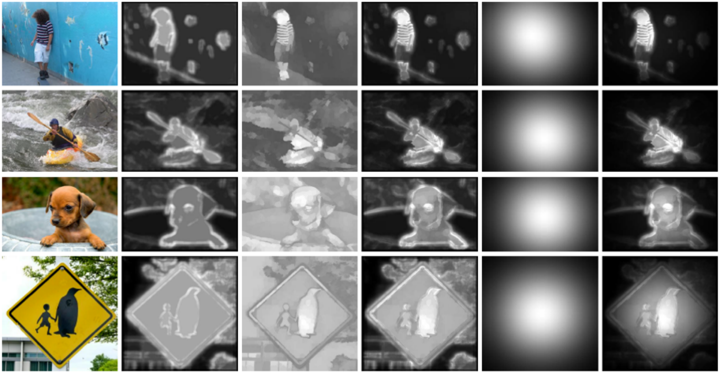
$\boldsymbol{P(p_x)}$	$\boldsymbol{C(p_x)}$	$\boldsymbol{G(p_x)}$
Pattern Distinctness Weighting Map	Color Distinctness Weighting Map	Gaussian Weighting Map

- Final Saliency

$$\boxed{S(p_x) = P(p_x) \cdot C(p_x) \cdot G(p_x)} \tag{5}$$

Putting it all together

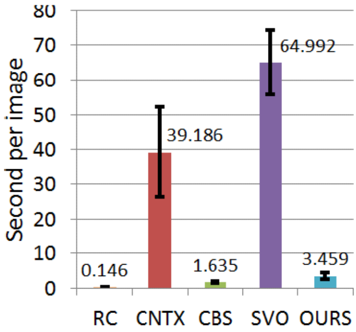
Results



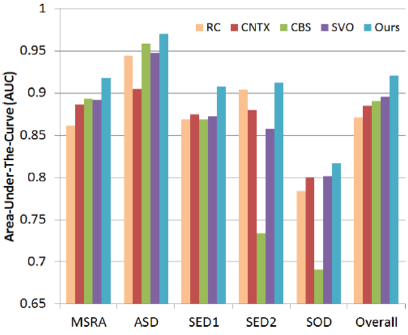
(a) Input (b) Pattern distinctness (c) Color distinctness (d) Pattern & Color (e) Organization priors (f) Final saliency

Outline

Performance Evaluation



Run-time Comparison



Accuracy Comparison

Outline

Conclusion

- Patch distribution plays an important role
- Combination of pattern and color distinctness
- Outperform the state-of-the-art results
- Not use high-level cues, such as face detection and object recognition
- Limit can be overcome by off-the-shelf recognition tools

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Q & A

Thank you for listening