Exploiting Information Theory for Filtering the Kadir Scale-Saliency Detector

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June 7th, 2007

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Outline

1. Introduction
2. Method
   - Entropy analysis through scale space
   - Bayesian filtering
   - Chernoff Information and threshold estimation
   - Bayesian scale-saliency filtering algorithm
   - Bayesian scale-saliency filtering algorithm
3. Experiments
   - Visual Geometry Group database
4. Conclusions

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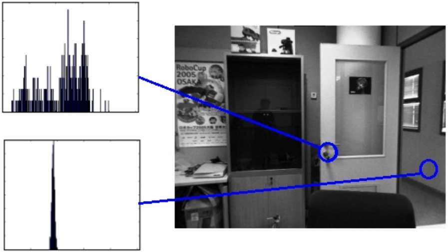
Local feature detectors

- Feature extraction is a basic step in many computer vision tasks
- Kadir and Brady scale-saliency
  - Salient features over a narrow range of scales
  - Computational bottleneck (all pixels, all scales)
- Applied to robot global localization $\rightarrow$ we need real time feature extraction

Salient features



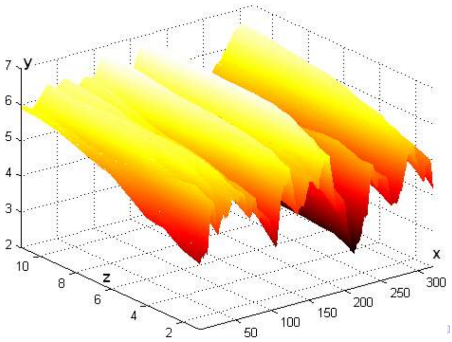
- $H_D(s, x) = -\sum_{d \in D} P_{d,s,x} log_2 P_{d,s,x}$
- Kadir and Brady algorithm (2001): most salient features between scales s_{min} and s_{max}

Outline

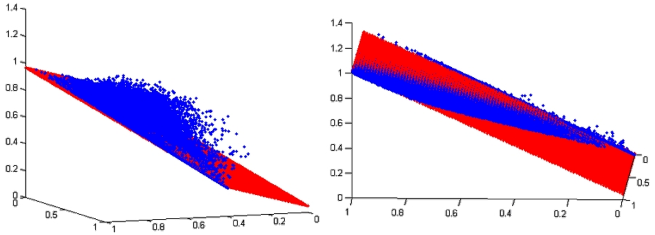
Entropy analysis through scale space

- Intuitive idea → entropy analysis through scale space

"Homogeneus regions at highest scale will probably be also homogeneus at lower scales"



Entropy analysis through scale space



$$f_1 = \frac{h_{max}}{H_{max}}$$

$$f_2 = \frac{h_{min}}{H_{min}}$$

$$f_3 = \frac{h_m}{H_{max}}$$

Estimation of multiple regression by plane Hough transform

$$f_3 = 0 \times f_2 + 1.01 \times f_1 + 0$$

Entropy analysis through scale space

Basic approach $\rightarrow$ threshold σ

Apply scale-saliency algorithm only to those pixels in

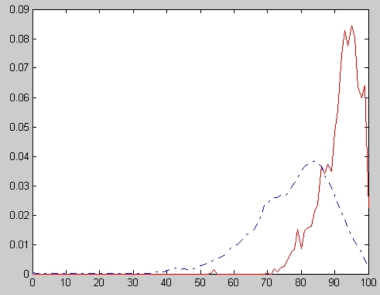
$$X = \left\{ x \middle| \frac{H_D(x, s_{max})}{H_{max}} > \sigma \right\}$$

where $H_{max} = max_x(H_D(x, s_{max}))$

- How to estimate threshold σ **before** applying scale-saliency to an image?
- Can an only threshold be applied to the whole set of images?

Bayesian filtering

- Konishi `et al.`, 2003 $\rightarrow$ bayesian edge detection
- Based on the calculation of distribution probabilities $P(\phi|on)$ and $P(\phi|off)$ where $\phi = H_D(s,x)/H_{max}$



Chernoff Information and threshold estimation

- Can an only threshold be applied to a set of images?
  - Chernoff information

$$C(p,q) = -\min_{0 \leqslant \lambda \leqslant 1} \log\left(\sum_{j=1}^{J} p^{\lambda}(y_j) q^{1-\lambda}(y_j)\right)$$

  - Low $C(P(\theta|on), P(\theta|off)) \rightarrow$ set of images is too heterogeneus

Chernoff Information and threshold estimation

- How to estimate a threshold **before** applying scale-saliency to a set of images?
  - Only $H_{max} = H_D(s_{max}, x)$ is needed
  - For a given threshold T, log-likelihood ratio criteria allows to discard image points:

$$\log(P(\phi|on)/P(\phi|off)) < T$$

  - Threshold T calculation by means of Kullback-Leibler distance (Cazorla *et al.*, 2002):

$$-D(P_{off}||P_{on}) < T < D(P_{on}||P_{off})$$

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Bayesian scale-saliency filtering algorithm

Training (for each image class)

- Estimate $P(\phi|on)$ and $P(\phi|off)$ using a set of training images
- Evaluate $C(P(\phi|on), P(\phi|off)) \rightarrow$ is the image class too heterogeneous?
- Caculate $D(P_{off}||P_{on})$ and $D(P_{on}||P_{off})$
- Select a threshold in the range $-D(P_{off}||P_{on}) < T < D(P_{on}||P_{off})$

Bayesian scale-saliency filtering algorithm

Filtering

- Calculate $\phi_x = \frac{H_{D_x}}{H_{max}}$ at s_{max} for each pixel x
- $X = \left\{ x \middle| \log \frac{P(\phi_x|on)}{P(\phi_x|off)} > T \right\}$
- Apply Kadir-Brady algorithm only to pixels $x \in X$

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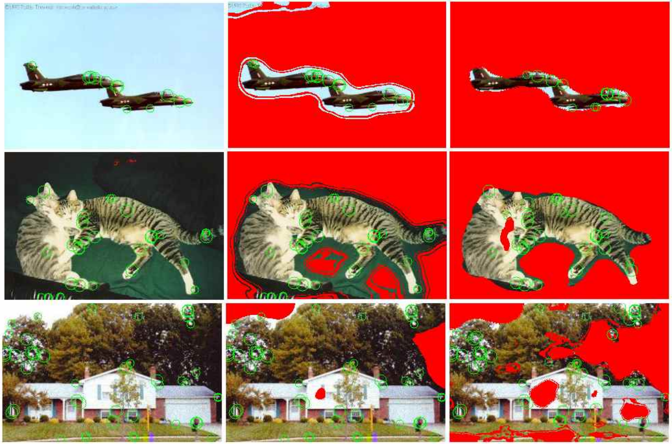
Visual Geometry Group database

- http://www.robots.ox.ac.uk/∽vgg/



Visual Geometry Group database

Test set	Chernoff	T	% Points	% Time	ϵ
airplanes_side	0.415	-4.98	30.79%	42.12%	0.0943
		0	60,11%	72.61%	2.9271
background	0.208	-2.33	15.89%	24.00%	0.6438
		0	43.91%	54.39%	5.0290
bottles	0.184	-2.80	9.50%	20.50%	0.4447
		0	23.56%	35.47%	1.9482
camel	0.138	-2.06	10.06%	20.94%	0.2556
		0	40.10%	52.43%	4.2110

Outline

Conclusions

- Kadir-Brady scale saliency algorithm
  - Computational bottleneck → all pixels, all scales
  - Intuitive idea → entropy analysis through scale space

"Homogeneus regions at highest scale will probably be also homogeneus at lower scales"

- Our method
  - Bayesian analysis → threshold T for each image class
  - Pixels having low entropy at highest scale are discarded
  - Scale-saliency algorithm is applied to the rest of image
  - Threshold T may vary in a precomputed range depending on application

Current work and future improvements

- New filters → filter cascade
- Multidimensional scale-saliency

- Combination of these two methods?

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