A New Feasible Approach to Multi-dimensional Scale Saliency

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October 2nd, 2009

Outline

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2. Method
3. Experiments
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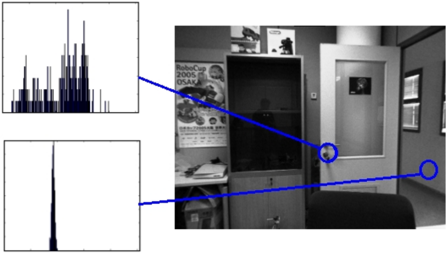
Local feature detectors

- Feature extraction is a basic step in many computer vision tasks
- Kadir and Brady scale-saliency
  - Widely used (Newton *et al.* ICRA 2006, Fergus *et al.* CVPR 2003)
  - Salient features over a narrow range of scales
  - Curse of dimensionality
- Previous scale saliency generalizations are too specific and not suitable for higher dimensions
- We present a naturally scalable approach (we report results on 31 dimensional data)

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}

Scale-saliency algorithm

Kadir and Brady scale-saliency algorithm (2001)

- For each pixel x
  - For each scale s between s_{min} and s_{max}
    - Calculate local entropy H_D from local PDF
  - Select the set of scales S where entropy is peaked
  - Weight the entropy values at S using the sum of absolute difference of PDFs
- Select the highest weighted entropy values

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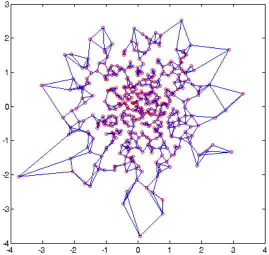
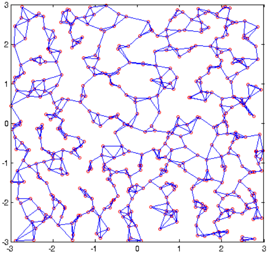
Multi-dimensional entropy estimation

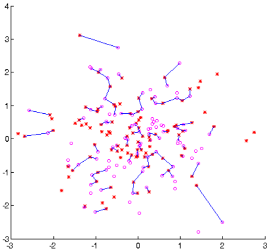
- Non plug-in methods
- Our previous approach
  - Shannon's entropy estimation from entropic graphs (edge lengths)
    - Rényi α-entropy (from Minimal Spanning Trees or K-Nearest Neighbour Graphs)
    - Leonenko estimation (from K-Nearest Neighbour Graphs)

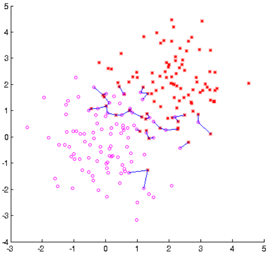




Multi-dimensional entropy estimation

- Our previous approach
  - Friedman and Rafsky's estimation of the Henze-Penrose divergence





KD-Partition entropy estimation

- Stowell *et al.* 2009
- Non plug-in method
  - Advantage: it does not require any distance computation
- Recursive and rectilinear data partition (KD-tree)

$$A = \{A_1, \ldots, A_p\}$$

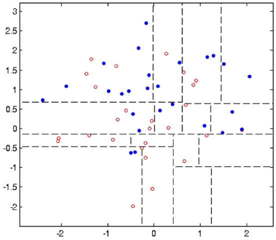
- Entropy estimated from the proportion of samples in each A_i

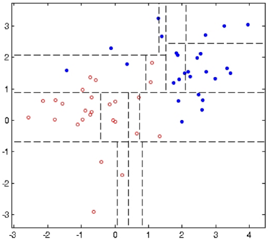
$$H = \sum_{i=1}^{p} \frac{n_i}{n} \log\left(\frac{n}{n_i}\mu(A_i)\right)$$

KD-Partition based divergence estimation

- Inspired by Friedman and Rafsky's test

$$D(X||O) = \sum_{i=1}^{p} \left| \frac{\frac{n_{x,i}}{N_x} - \frac{n_{o,i}}{N_o}}{2} \right|$$





$D(X||O) = 0.3642$ $\qquad$ $D(X||O) = 0.7692$

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The multidimensional scale-saliency algorithm

Input: A m-dimensional array I containing m features for each pixel of the image
Output: An array HW containing weighted entropy values for all pixels on image at each scale

```
foreach pixel x of image do
    foreach scale s_i between s_min and s_max do
        (1) Create a m-dimensional sample set X_i = {x_i} from the local
        neighborhood of pixel x at scale s_i in I;
        (2) Apply KD-partition to X in order to estimate entropy H(s_i)
        if i > s_min + 1 then
            if H(s_{i-2}) < H(s_{i-1}) > H(s_i) then
                (* Entropy peak *)
                (4) KD-partition divergence: W = s^2/(2s-1) D(X_{i-1}||X_{i-2});
                (5) HW(s_{i-1}, x) = H(s_{i-1}) · W;
            end
            else
                (6) HW(s_{i-1}, x) = 0;
            end
        end
    end
end
```

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Image databases

- Bristol hyperspectral image database (http://psy223.psy.bris.ac.uk/hyper/)


- Affine covariant regions dataset (http://www.robots.ox.ac.uk/∼vgg/research/affine/)


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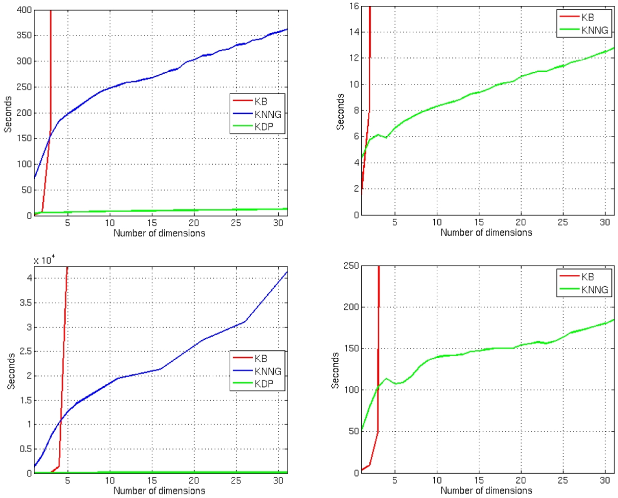
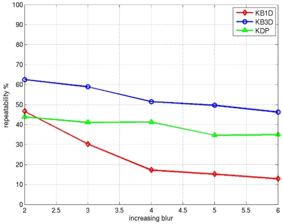
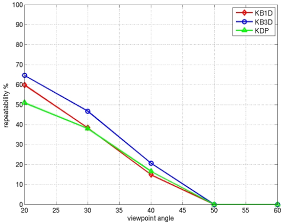
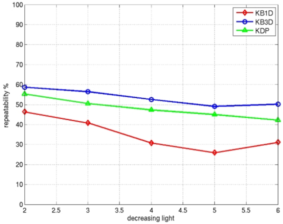
Execution time

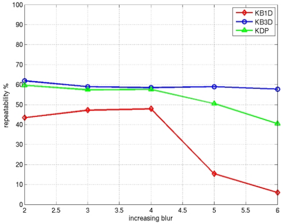


Detector quality

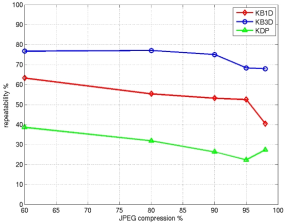


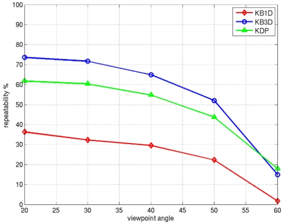


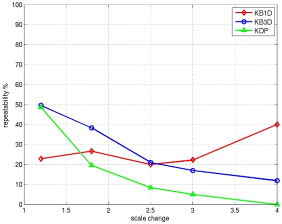




Detector quality







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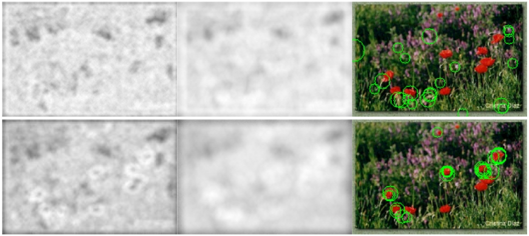
Conclusions

- We presented a new and feasible multi-dimensional scale saliency algorithm
- Entropy estimation by means of KD-Partition algorithm
- Divergence measure based on KD-Partition and inspired by Friedman and Rafsky's test
- Remarkably decrease of execution time
- Detector quality is not strongly affected

Future work

- Impact of high-dimensional data on computer vision problems
  - Video analysis (A. Oikonomopoulos, I. Patras, M. Pantic: Spatiotemporal saliency for human action recognition. ICME 2005)
  - Texture categorization (S. Lazebnik, C. Schmid, J. Ponce: A sparse texture representation using local affine regions. PAMI 2005)



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