Analysis of the Multi-Dimensional Scale Saliency Algorithm and its Application to Texture Categorization

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Abstract

- A new approach for multi-dimensional Scale Saliency (MDSS) was lately introduced [1]
- The MDSS algorithm is based on alternative entropy and divergence estimation methods whose complexity does not exponentially increase with data dimensionality
- In this paper:
  - We apply the MDSS algorithm to the texture categorization problem
  - We provide further experiments in order to assess the suitability of different estimators
  - We propose a new divergence measure based on the k-d partition algorithm

Introduction

- The work in this paper is focused on the Scale Saliency algorithm by Kadir and Brady [2]
  1. Shannon's entropy is estimated from an intensity pdf for all pixels x in the image, using all scales s in a range of scales between s_{min} and s_{max}. Entropy at scale s is computed from the grayscale intensity pdf of the circular region R_x of radius s, centered over x
  2. Entropy peaks (local maxima in scale space) are selected
  3. Entropy peaks are weighted by means of a self-dissimilarity metric between scales
  4. A subset of the salient features is selected, in order of weighted entropy. These selected features are the most salient features of the image.
- The application of the algorithm summarized above to higher dimensional data is straightforward but unfeasible (curse of dimensionality)

MDSS Based on K-Nearest Neighbour Graphs

- Each pixel $x_i \in X$ is represented as a d-dimensional vector
- The neighbourhood R_x of a pixel is represented as an undirected and fully connected graph $G = (V, E)$, being the nodes $v_i \in V$ the d-dimensional vectors representing $x_i \in R_x$ and E the set of edges connecting each pair of nodes
- The weight of each edge is the Euclidean distance in $\mathcal{R}^d$ between its two incident nodes
- Entropy estimation from KNNG by means of the measure defined by Kozachenko and Leonenko [3]

$$\hat{H}_{N,k} = \frac{1}{N}\sum_{i=1}^{N} \log\left((N-1)e^{-\psi(k)} B_d(\rho_{k,N-1}^{(i)})^d\right) \quad , \qquad (1)$$

- Dissimilarity between scales (divergence) by means of the Friedman and Rafsky test [4]

MDSS Based on the k-d Partition Algorithm

- Entropy estimation based on the k-d partition algorithm by Stowell *et al.* [5]
- New divergence measure inspired by the k-d partition algorithm and the total variation distance [6]
  - Apply the partition scheme of the k-d partition algorithm to the set of samples $X \bigcup O$
  - The result is a partition A of $X \bigcup O$, being $A = \{A_j | j = 1, \ldots, p\}$

$$D(O||X) = \frac{1}{2}\sum_{j=1}^{p} |p_j - q_j| \quad . \qquad (2)$$

Experimental Results

- we introduce additional experiments to those shown in [1], that were aimed to compare the computational time of both MDSS approaches and the quality of the extracted features. Results are shown in Fig. 1, Fig. 2 and Fig. 3
- MDSS applied in conjunction with the Lazebnik *et al.* [7] texture representation to the texture categorization problem (Fig. 4)
  - Entropy estimation from 15D data obtained by means of a Gabor filter bank applied to all pixels

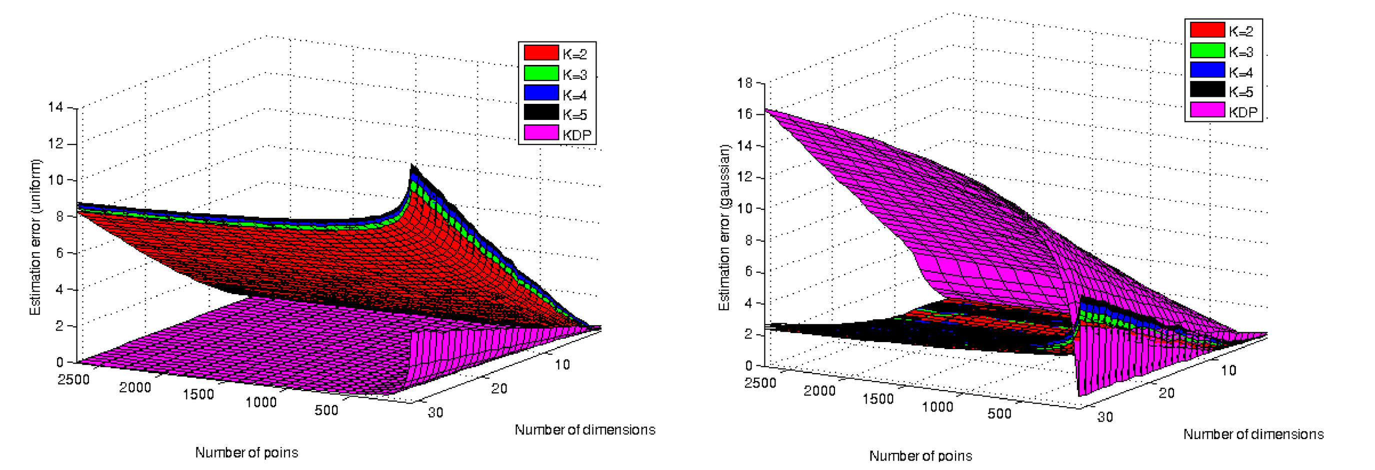

Figure 1: K-d partition (KDP) and Leonenko *et al.* method (for $k = 2 \ldots 5$) estimation bias for an uniform distribution in the range $[-3,3]^d$ (left) and a Gaussian distribution with zero mean and $\Sigma = I$ (right).

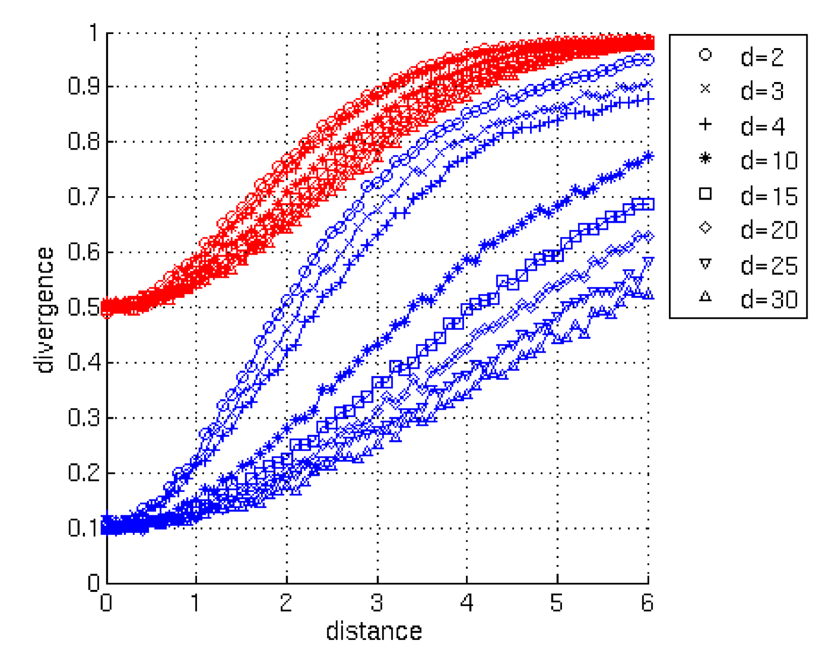

Figure 2: Divergence estimation results using Friedman-Rafsky test (red) and k-d partition divergence (blue), for different data dimensionalities (d).

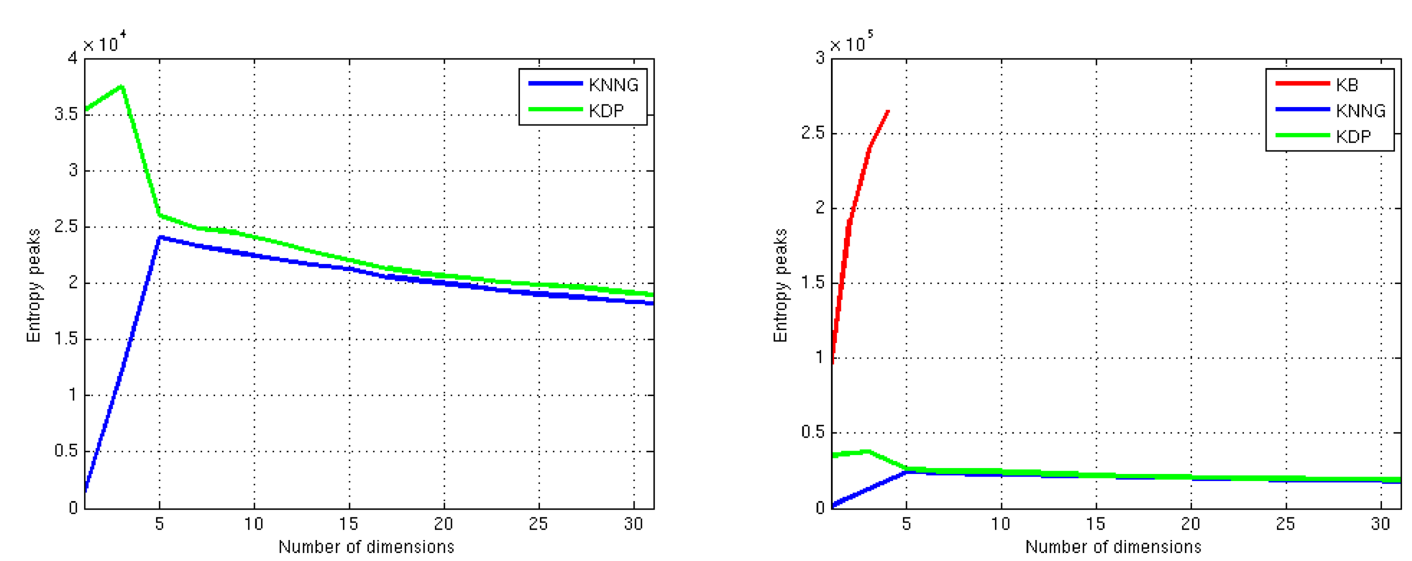

Figure 3: Mean number of detected entropy peaks during Leonenko based MDSS (KNNG), k-d partition based MDSS (KDP) and Kadir and Brady Scale Saliency (KB) for increasing data dimensionality.

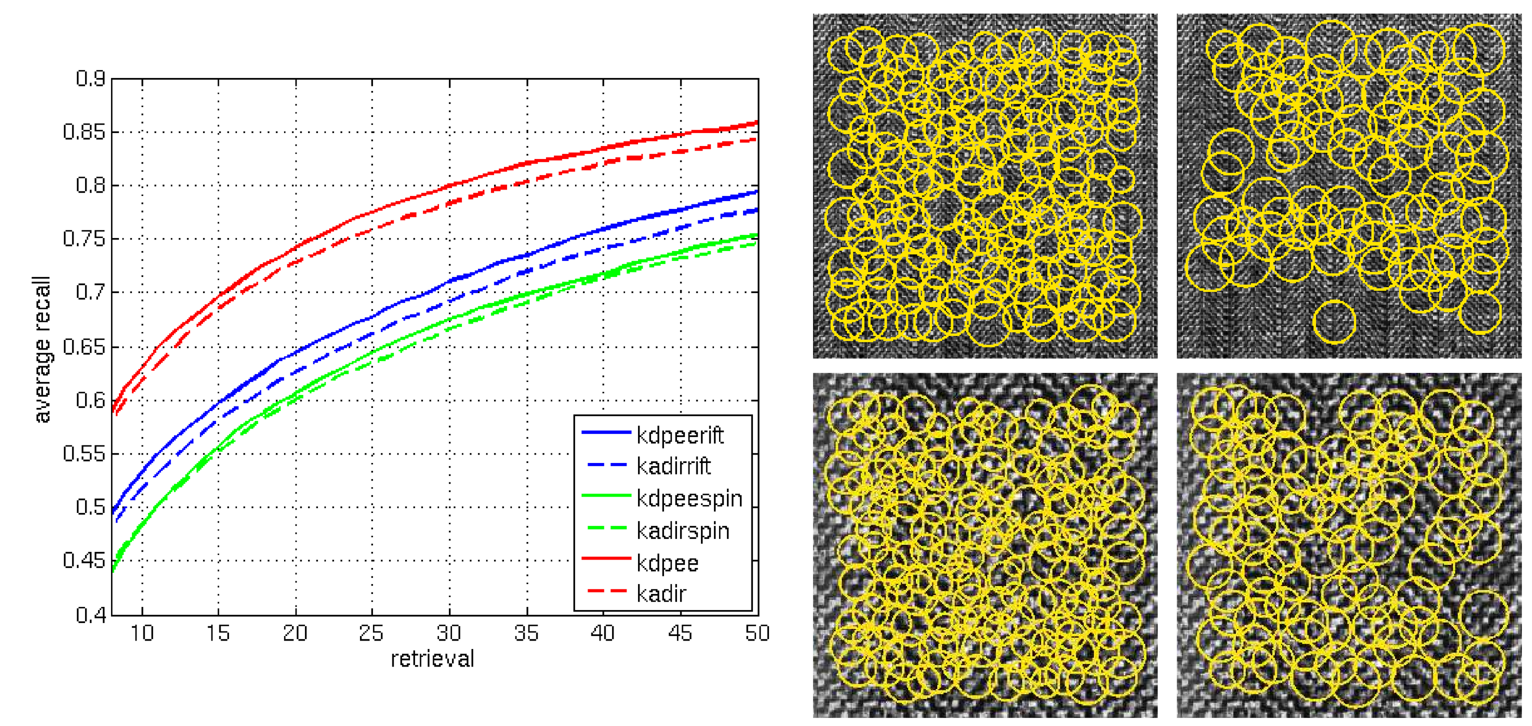

Figure 4: Left: results of the texture categorization experiment. Right: output of the MDSS algorithm from 15D data (left) and the Scale Saliency algorithm from grayscale intensities (right), for two example texture images. In both cases the 150 most salient features (after non maximum suppression) were selected.

Conclussions and Future Work

- Our analysis shows that the k-d partition approach should be preferred over the graph based approach
- We introduced a new divergence estimation method based on the k-d partition algorithm and the total variation distance, and we experimentally demonstrated its suitability
- We showed a practical application of our approach in the context of texture categorization
- Our future work is addressed to evaluate the application of multi-dimensional data processing in other computer vision problems, like video processing or image retrieval. In the texture categorization context, we should also study the impact of using different Gabor filter banks, or even different input data. This is a combinatorial problem that may be treated with Machine Learning methods like feature selection.

References

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