

Nonparametric Scene Parsing with Adaptive Feature Relevance and Semantic Context

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Related Works

- J. Tighe and S. Lazebnik. Superparsing: Scalable nonparametric image parsing with superpixels. In ECCV (5), pages 352–365, 2010.
- D. Eigen and R. Fergus. Nonparametric image parsing using adaptive neighbor sets. In CVPR, pages 2799–2806, 2012.
- D. Ramanan and S. Baker. Local distance functions: A taxonomy, new algorithms, and an evaluation. PAMI, 33(4):794–806, 2011.

Approach

- Local patches (gradient orientation, color, location features)
- k-NN
- Semantic Labelling

Semantic segmentation with small superpixels

Posterior probability of labelling L

$$P(\mathbf{L}|\mathbf{A}) = \frac{P(\mathbf{A}|\mathbf{L}) P(\mathbf{L})}{P(\mathbf{A})}.$$

Estimated value of labelling L as MAP

$$\underset{\mathbf{L}}{\operatorname{argmax}} P(\mathbf{L}|\mathbf{A}) = \underset{\mathbf{L}}{\operatorname{argmax}} P(\mathbf{A}|\mathbf{L}) P(\mathbf{L}).$$

Superpixels and features



Retrieval set

- Global image features
 - o GIST
 - Spatial Pyramid of quantized SIFT
 - RGB-Color Histograms
- Euclidean distance from the query image
- Ranking
- Re-ranking

Appearance likelihood

Naive Bayes assumption

$$P(\mathbf{A}|\mathbf{L}) \approx \prod_{i=1}^{S} P(\mathbf{a}_i|l_i).$$

Label likelihood score

$$L(\mathbf{a}_i, l_j) = \frac{n(l_j, N_{ik})/n(l_j, G)}{n(\overline{l_j}, N_{ik})/n(\overline{l_j}, G)}$$

- $\bar{l_j} = L \setminus l_j$ is the set of all labels excluding l_j ;
- N_{ik} is a neighbourhood around a_i with exactly k points in it;
- n(l_j, N_{ik}) is the number of superpixels of class l_j inside N_{ik};
- n(l_j, G) is the number of superpixels of class l_j in the set G

Weighted k-NN

Color, SIFT and location

$$\boldsymbol{d}_{f}^{ij} = [\boldsymbol{d}_{c}^{ij}, \boldsymbol{d}_{s}^{ij}, \boldsymbol{d}_{l}^{ij}]^{\mathsf{T}}$$

Weighted distance

$$d_w^{ij} = w^{\top} d_f^{ij}$$
 $w = [w_1, w_2, w_3] \in \Re^3$

Weight computation

i: feature channel N: neighbourhood x: query pointc: influence of weights

$$r_i(\mathbf{z}) = \sum_{l_j=1}^{nL} \frac{(P(l_j|\mathbf{z}) - \bar{P}(l_j|x_i = z_i))^2}{\bar{P}(l_j|x_i = z_i)}$$

$$\bar{r}_i(\mathbf{x}_0) = \frac{1}{|N(\mathbf{x}_0)|} \sum_{\mathbf{z} \in N(\mathbf{x}_0)} r_i(\mathbf{z})$$

$$w_i(\mathbf{x}_0) = \frac{exp(cR_i(\mathbf{x}_0))}{\sum_{p=1}^{m} exp(cR_p(\mathbf{x}_0))}$$

Query based algorithm

1) Initialize w to uniform weights

- At query point x₀, find set N₀ of K₀ nearest neighbors using current w
- For each feature channel, compute relevance estimate using points in N₀
- 4) Update w using relevance estimates from 3
- 5) Repeat steps 2-4 (five times in our experiments)

Semantic retrieval set





Experiments

Datasets

- SiftFlow 2688 images with 33 semantic categories
 - 2488 for training 200 for testing
- SUN09 fully labeled, 107 semantic categories
 - 4352 for training 4310 for testing
- Google Street View labeled data, 320 images
 - 160 for training 160 for testing
- Stanford Background semantic and geometric labeled 715 images
 - 572 for training 143 for testing

Results

System	Per-Pixel	Per-Class
Liu et al. [15]	76.7	-
Tighe et al. [26]	76.9	29.4
Eigen et al. [4]	77.1	32.5
UKNN-MRF	75.6	27.9
WKNN-MRF	77.2	29.3
WLKNN-MRF	78.5	32.0
WAKNN-MRF	79.2	33.8
WKNN-MRF (with HOG)	76.7	27.4

Table 1. Semantic labelling performance on the SiftFlow dataset

Results

Dataset and System	Per-Pixel	Per-Class
SUN09		
Choi et al. [1]	33.0	10.6
[25] CascALE Expert	49.3	16.7
[25] CascALE Sharing	52.8	15.2
WKNN-MRF	49.5	8.7
WAKNN-MRF	53.1	12.1
Google Streetview		
Zhang et al. [32]	88.4	80.4
Zhang et al. [31]	93.2	73.1
Singh et al. [24]	94.4	81
WAKNN-MRF	93.7	76.4
Stanford background		
[6] Pixel CRF	74.3	66.6
[6] Region Energy	76.4	65.5
[20] Leaf Level	72.8	58.0
[20] Hierarchy	76.9	66.2
WKNN-MRF	73.6	61.2
WAKNN-MRF	74.1	62.2

Table 2. Performance on the SUN09, Google-Streetview and Stanford background datasets.

Results



W - 78.7%, R - 87.2%

THANK YOU!