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Web-based Learning of Naturalized Color Models for Human-Machine Interaction

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Overview

Motivation



- Recognizing and naming attributes is essential for HRI
- Large annotated data sets required to learn robust models
- Use Internet queries to retrieve training data and learn natural, robust models for HRI (different domain!)
- Smaller model trained on raw data provides equal/better performance
- Probabilistic HSL model for domain adaptation combined with X² ranking



Model

Probabilistic HSL Color Observation Model

- Images retrieved through Internet image search engines are often synthetic or highly processed
- Improve quality with a transformation that adds noise to approach natural distributions for artificial images
- 1) Probabilistic Hue-Saturation-Lightness color model to reflect degree of randomness of "measured" colors $l_d = l$

$$f_{\mathcal{VM}}(x;\mu,\kappa) = \frac{1}{2\pi I_0(\kappa)} e^{\kappa \cos(x-\mu)} \Big|_{\mu=h_0}$$
$$f_{\sigma \mathcal{M}}(x;\mu,\sigma,\alpha,b) = \frac{\frac{1}{\sigma} f_{\mathcal{N}}(\frac{x-\mu}{\sigma})}{\frac{1}{\sigma} f_{\mathcal{N}}(\frac{x-\mu}{\sigma})} \Big|_{\mu=h_0}$$

Learning Color Terms

- 11 basic color terms in English (other colors are derived)
 Train color term models on randomized training data
- Train initial models and use X² ranking to remove outliers and images degraded by a huge amount of background

$$d_{\chi^2}^{zd}(P'(\cdot|z), P(\cdot|d)) = \sum_{w \in W} \frac{(P(w|d) - m)^2}{m} \quad m = \frac{P'(w|z) + P(w|d)}{2}$$
$$R_{\chi^2}^{zd} = \frac{d_{\chi^2}^{zd}}{\min_{z' \neq z} d_{\chi^2}^{z'd}}$$



$f_{\mathcal{T}\mathcal{N}}(x;\mu,\sigma,a,b) = \frac{\sigma}{F_{\mathcal{N}}(\frac{b-\mu}{\sigma}) - F_{\mathcal{N}}(\frac{a-\mu}{\sigma})} \Big|_{\substack{\mu=s_d\\a=0\\b=1}}^{\mu=s_d}$

2) κ and σ define the degree of randomness and the **randomized HSL transform resamples** data for training $\kappa = (1-s)^{-p_s}(1-b)^{-p_b} - 1$ $\sigma = \kappa^{-1/2}$ $b = 2\min(l, 1-l) \in [0, 1]$



2) Probabilistic latent semantic analysis with a latent background topic to learn the color models

 $P(w|d, l_d = z) = \alpha_d P(w|l_d = z) + (1 - \alpha_d) P(w|bg)$

3) Assign color term with highest likelihood (uniform prior)

Evaluation

Data

Training with 512 Google images for each color term



Results						
Method	Space	Cars	Shoes	Dresses	Pottery	Total
Randomized						
X ² rank	HSL	73.63	92.73	88.18	79.01	83.41
pLSA-bg	HSL	69.18	87.36	87.36	77.36	81.32
Deterministic						
X ² rank	HSL	68.18	91.81	87.27	76.36	80.90
pLSA-bg	HSL	66.36	90.00	85.45	73.63	79.31
Reference						
Weijer	L*a*b*	71.82	92.73	86.36	83.64	83.64
Human	Brain	92.73	90.18	91.99	87.82	90.64

Evaluation with E-Bay data set (10 images per term)
E-Bay data set extended with labels assigned by 5 persons





 32x8x8 HSL histogram bins; no preprocessing of images (Weijer et al.: 10x20x20 L*a*b*; foreground segmentation) X² rank color labeling behavior closer to human, i.e distance between confusion matrices is 0.57 and 0.73, resp.

DICTA 2010 Sydney, Australia http://cvhci.anthropomatik.kit.edu http://www.irf.tu-dortmund.de/cms/en/IS