

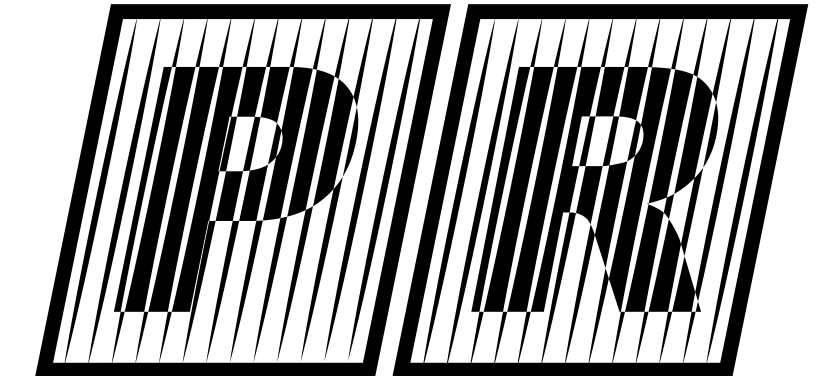
Image Retrieval Measures Based on Illumination Invariant Textural MRF Features

Pavel Vácha Michal Haindl

{vacha, haindl}@utia.cas.cz



Institute of Information Theory and Automation
Academy of Sciences of the Czech Republic, Prague, Czech Republic, CZ182 08



Abstract

Content-based image retrieval (CBIR) systems target database images using feature similarities with respect to the query. We introduce fast and robust image retrieval measures that utilise novel illumination invariant features extracted from three different Markov random field (MRF) based texture representations. These measures allow retrieving images with similar scenes comprising colour textured objects viewed with different illumination brightness or spectrum. The proposed illumination insensitive measures are compared favourably with the most frequently used features like the Local Binary Patterns, steerable pyramid and Gabor textural features, respectively. The superiority of these new illumination invariant measures and their robustness to added noise are empirically demonstrated in the illumination invariant recognition of textures from the Outex database.

Problem Formulation

Illumination invariant retrieval of colour textures:

- Position of viewpoint and illumination source are fixed.
- Illumination spectrum and brightness are unknown and they can change arbitrary.

Proposed Solution

- Illumination invariants computed from MRF texture representations.

CAR Texture Models:

$$Y_r = \sum_{s \in I_r} A_s Y_{r-s} + \epsilon_r$$

Y_r vector at texture position r

I_r contextual causal or unilateral neighbourhood

A_s unknown parameter matrices (diagonal for 2D models)

ϵ_r white noise with zero mean and unknown covariance matrix

$Z_r = [Y_{r-s}^T : \forall s \in I_r]^T$ data vector

$\gamma = [A_1, \dots, A_\eta]$, $\eta = \text{card}(I_r)$

Analytical recursive Bayesian estimation of γ .

Illumination Invariants

Proposed illumination invariants:

- trace: $\text{tr } A_m$, $m = 1, \dots, \eta K$
- eigenvalues: $\nu_{m,j}$ of A_m , $j = 1, \dots, C$

- $\alpha_1: 1 + Z_r^T V_{zz}^{-1} Z_r$

- $\alpha_2: \sqrt{\sum_r (Y_r - \gamma Z_r)^T \lambda^{-1} (Y_r - \gamma Z_r)}$

- $\alpha_3: \sqrt{\sum_r (Y_r - \mu)^T \lambda^{-1} (Y_r - \mu)}$

μ mean value of vector Y_r

λ, V_{zz} texture statistics, details in the article

C, K number of spectral planes, pyramid levels



Examples of illumination invariant retrieval on textures from OuTex database [1].

The Retrieval Algorithm

- Analysis
 1. Perform K-L transformation (for 2D models).
 2. Build Gaussian pyramid on the texture.
 3. Find the parametric representation of each pyramid level.
 4. Compute illumination invariants from the estimated parameters.
 5. Form feature vector Θ from the invariants.
- Retrieval
 1. Find the n nearest textures to a given target texture based on the L_1 norm
 $j^* = \arg \min_j |\Theta - \Theta_j|$.

Experiments

Illumination invariant retrieval on textures from University of Oulu texture database [1], where each texture is illuminated with three different illuminations: horizon sunlight, incandescent CIE A, fluorescent TL84.

Performance of illumination invariant retrieval measured by recall rate [%] with three nearest textures retrieved:

| method | added Gaussian noise σ | | | |
|---|-------------------------------|-------------|-------------|-------------|
| | 0 | 2 | 4 | 8 |
| Gabor f., grey img, norm. | 53.4 | 58.1 | 58.7 | 56.1 |
| Opponent Gabor f., norm. | 46.9 | 45.0 | 40.9 | 37.8 |
| Steerable pyramid, norm. | 41.2 | 41.0 | 40.5 | 39.4 |
| LBP _{8,1+8,3} , grey img. | 83.1 | 66.0 | 56.0 | 50.3 |
| GMRF-KL, $\alpha_4 \alpha_5$ | 82.7 | 78.2 | 70.1 | 56.5 |
| 2CAR-KL 2x, $\alpha_1 \alpha_2 \alpha_3$ | 89.2 | 86.3 | 80.5 | 68.7 |
| 3CAR 2x, $\alpha_1 \alpha_2 \alpha_3$ | 85.1 | 82.6 | 77.5 | 66.5 |
| 2CAR-KL 2x, $\alpha_1 \alpha_2 \alpha_3, L_{1\sigma}$ | 94.2 | 92.9 | 89.2 | 81.7 |
| 3CAR-KL 2x, $\alpha_1 \alpha_2 \alpha_3, L_{1\sigma}$ | 90.3 | 88.3 | 81.8 | 69.2 |

Conclusions

- ⊕ Single training image per class.
- ⊕ Invariant to brightness and illumination spectrum.
- ⊕ Robust to added Gaussian noise.
- ⊕ Recursive analytical solution (CAR models).
- ⊕ Outperforms alternative methods.

References

- [1] T. Ojala, T. Mäenpää, M. Pietikäinen, J. Viertola, J. Kyllönen, and S. Huovinen. Outex - new framework for empirical evaluation of texture analysis algorithms. In *Proc. of the 16th ICPR*, pp. 701–706, August 2002.