

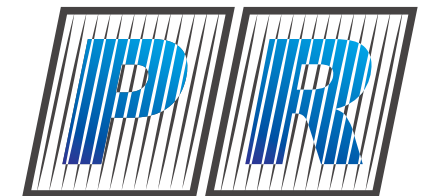
Illumination Invariant and Rotational Insensitive Textural Representation

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

We propose an illumination invariant and rotation insensitive texture representation based on a Markovian textural model. A texture is aligned with its dominant orientation and textural features are derived from fast analytical estimates of Markovian statistics. We do not require any knowledge of illumination direction or spectrum. This makes our method suitable for computer analysis of real scenes, where appearance of materials depends on their orientation towards the illumination source. Our method is tested on the most realistic visual representation of natural materials - the bidirectional texture function (BTF), using data from the CURET database, where it outperforms the alternative leading illumination invariant Local Binary Patterns (LBP) and texon MR8 methods, respectively.

Problem Formulation

Texture recognition robust to illumination and rotation variations:

- Illumination spectrum and brightness are unknown and variable.
- Illumination position is unknown and variable.
- Viewpoint position changes are limited to texture rotation.
- Low number of training samples (1 – 4).
- Conditions close to real world.

Proposed Solution

- Detection of dominant orientation based on histogram of gradient orientations $[0^\circ, 180^\circ)$.
- 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 of pixel values at texture position r

I_r contextual 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

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

Invariants to Illumination Spectrum:

- 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

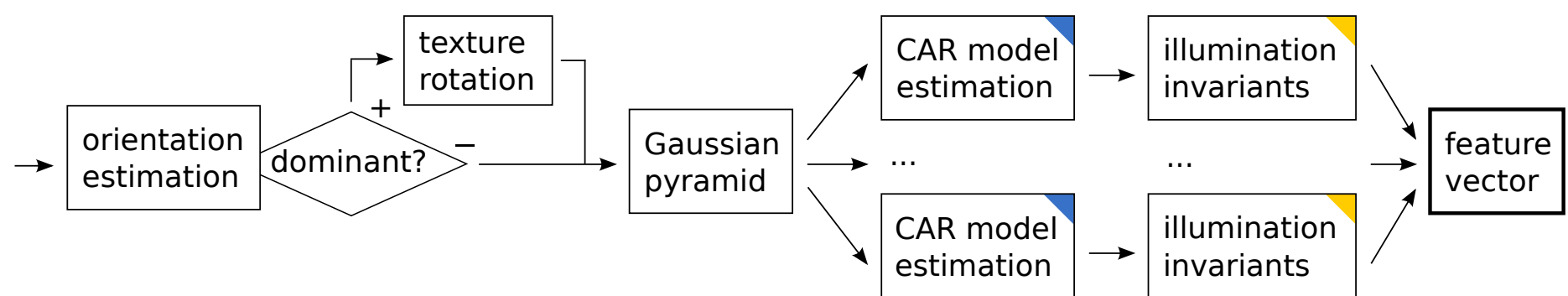
λ, V_{zz} texture statistics, details in the article

C, K number of spectral planes, pyramid levels

Real scene appearance under different illumination conditions



Texture analysis algorithm



Experiments

Recognition of textures from Columbia-Utrecht Reflectance and Texture Database (CURET):

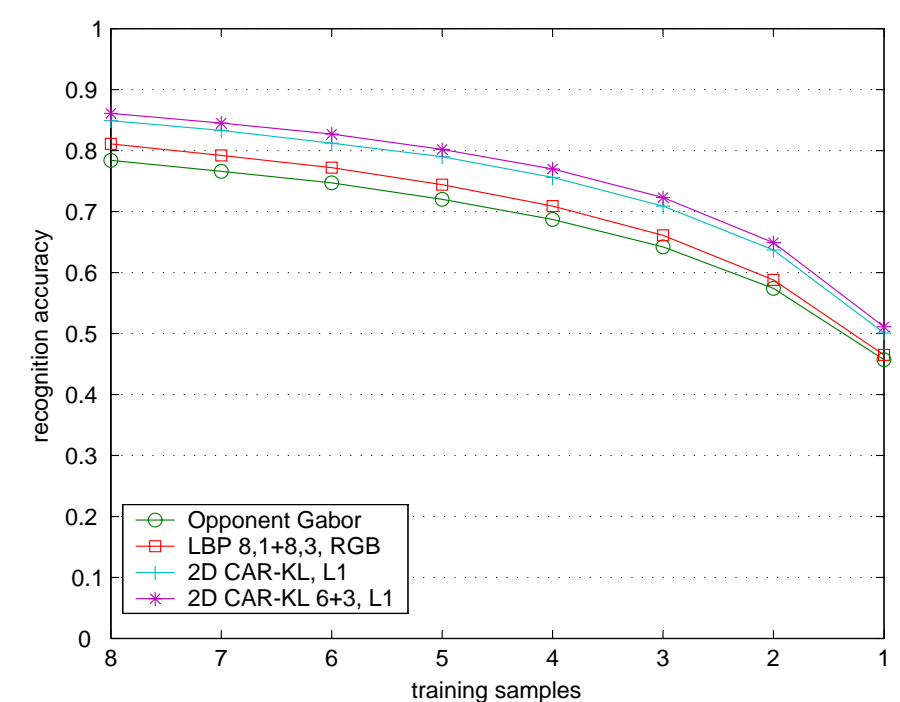
- 92 samples with different illumination and viewpoint positions per material.
- 61 real-world materials.
- 5612 images in total.
- 1000 random selections of training images.

Correct classification [%] using 4 random training images per material:

method	accuracy	vector size
MR8-LINC [1]	67	600
Opponent Gabor features	68.7	252
LBP _{8,1+8,3} , grey	66.9	512
LBP _{8,1+8,3} , RGB	70.9	1536
LBP _{16,2} ^u , RGB	68.7	729
2D CAR-KL, L ₁	75.6	260
2D CAR-KL 6+3, L₁	77.0	392
3D CAR 6+3, L ₁	72.4	344

[1] G. J. Burghouts and J. M. Geusebroek, "Material-specific adaptation of color invariant features," *Pattern Recognition Letters*, vol. 30, pp. 306–313, 2009.

Correct classification for different numbers of random training images:



Conclusions

- ⊕ Invariant to illumination brightness and spectrum.
- ⊕ Robust to illumination direction.
- ⊕ Insensitive to texture rotation.
- ⊕ Only one training image per material is required.

Demo at <http://cbir.utia.cas.cz>