Illumination Invariants Based on Markov Random Fields

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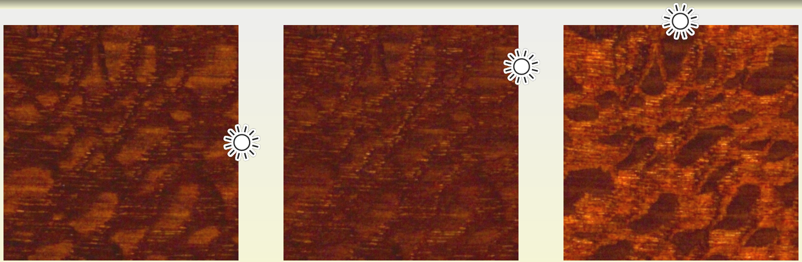
Real Scene – Illumination Dependency

Material Illumination Variance



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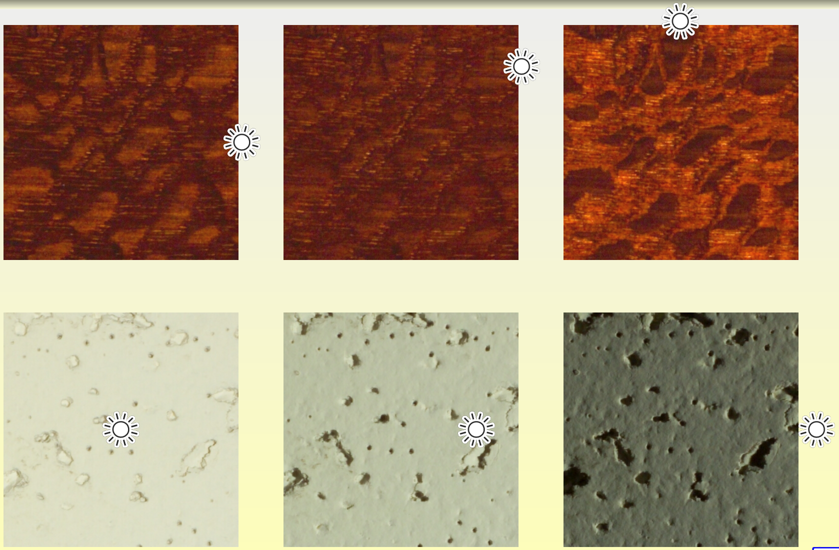

Proposed Method Properties

Illumination variation:

- Illumination brightnesses .... invariant
- Illumination spectrum .... invariant
- Illumination direction .... robust

Unknown illumination conditions.

Single training image per material (texture).

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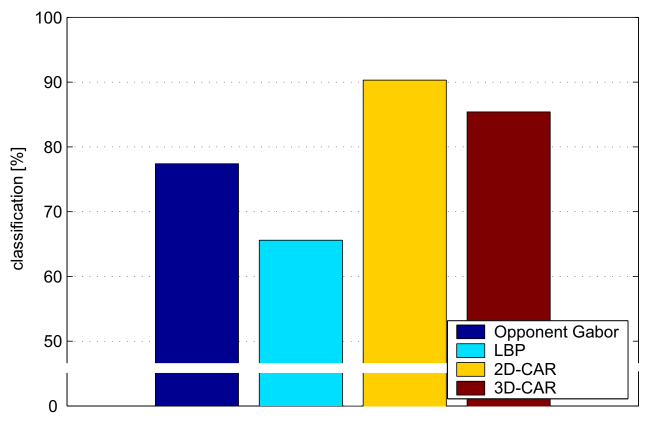
10 % Improvement



Correct classification [%] - changing illumination direction.

Method

1. Gaussian pyramid with K levels
2. Markovian texture representation
3. Estimate of MRF model parameters
4. **Illumination invariants are derived from the model parameters**
5. Illumination invariant feature vectors
6. Feature vectors are compared in L_1 / FC norms

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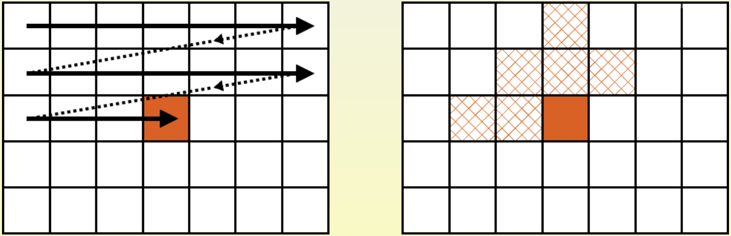
MRF-CAR Model

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

r, s	pixel multiindices, $r = $ (row, column)
Y_r	vector value (R, G, B) at texture position r
I_r	causal contextual neighbourhood with size η
A_s	**unknown parameter matrices**
ϵ_r	white noise with zero mean and unknown covariance matrix

Model Parameter Estimation

Analytical recursive Bayesian estimate for all statistics (A_s, ϵ)



movement neighbourhood

Illumination Invariance

Two images Y, $\tilde{Y}$ of the same Lambertian surface illuminated with different illumination brightnesses and spectra:

$$Y_r = B\tilde{Y}_r$$

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

$$B\tilde{Y}_r = \sum_{s \in I_r} \tilde{A}_s \, B \, \tilde{Y}_{r-s} + \tilde{\epsilon}_r$$

$$\boxed{A_s \approx B^{-1} \tilde{A}_s \, B}$$

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Illumination Invariants

1. trace: $\mathrm{tr}\, A_m^k$ $\quad m = 1, \ldots, \eta\,, k = 1, \ldots, K$
2. eigenvalues: $\nu_{m,j}$ of A_m^k $\quad m = 1, \ldots, \eta\,, k = 1, \ldots, K,$ $j = 1, \ldots, C$

η size of contextual neighbourhood
C number of spectral planes ($C = 3$)
K number of Gaussian pyramid levels

Illumination Invariants

3. $\alpha_1 = 1 + Z_r^T V_{zz}^{-1} Z_r$

4. $\alpha_2 = \sqrt{\sum_r \left(Y_r - \sum_{s \in I_r} A_s Y_{r-s} \right)^T \lambda^{-1} \left(Y_r - \sum_{s \in I_r} A_s Y_{r-s} \right)}$

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

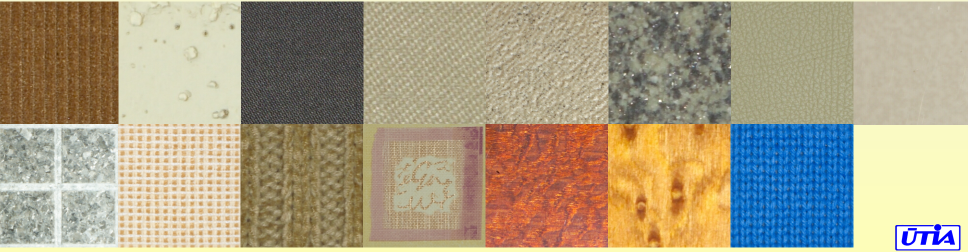
$Z_r = [Y_{r-i}^T : \forall i \in I_r]^T$ data vector

λ, V_{zz} model statistics
μ mean value of vector Y_r

Experimental Setup

Textures:

- University of Bonn BTF Database
- 81 illumination directions
  declination angles $[0^\circ, \ldots, 75^\circ]$,
  azimuth angles $[0^\circ, \ldots, 360^\circ]$
- 15 materials



Experimental Setup

Classification:

- Single training image per material
- Nearest neighbour classification

Tests:

1. Training image with top illumination
2. 10^5 random samples of training images
   3 test sets - viewpoint declination angles $0°, 30°, 60°$

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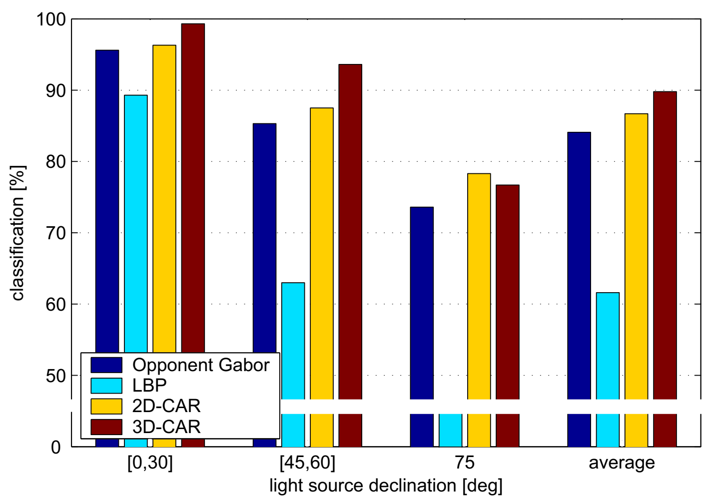
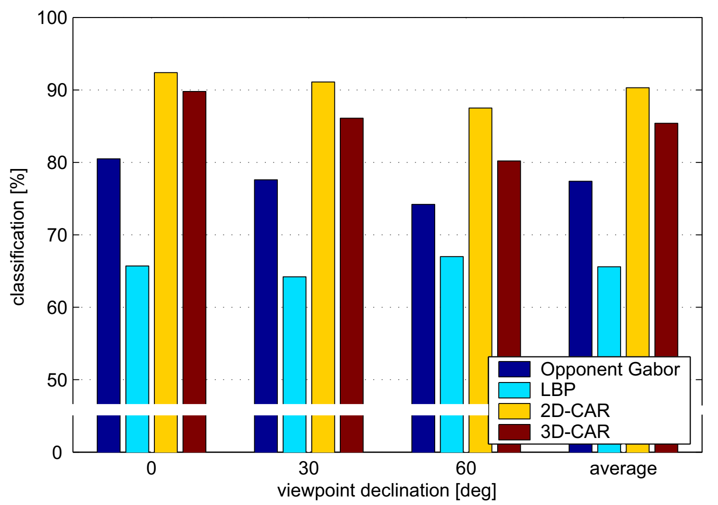
Results – Top Training Image



Correct classification with training image fixed to the top illumination, viewpoint angle 0°

Results – Random Training Images



Correct classification [%] - one training image per texture

Conclusion

Summary:

- Single training image per material
- Invariant to illumination brightness and spectrum
- Robust to illumination direction
- Illumination knowledge not needed

- 10% improvement over Gabor features / LBP methods

Future Plans:

- Extension to images
- Integration to some CBIR system

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Questions?

http://ro.utia.cz/dem.html

References

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