Texture Recognition using Robust Markovian Features

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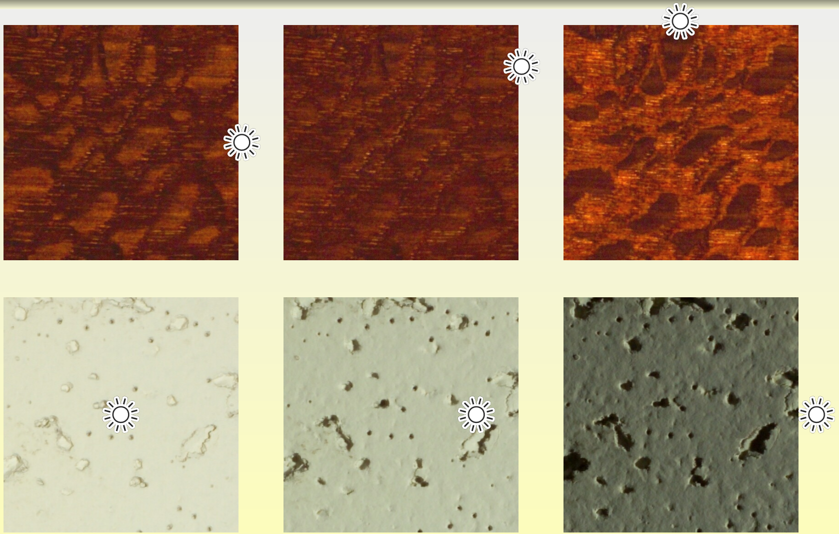
Real Scene – Illumination Dependency

Material Appearance Variation



[University of Bonn BTF Database]

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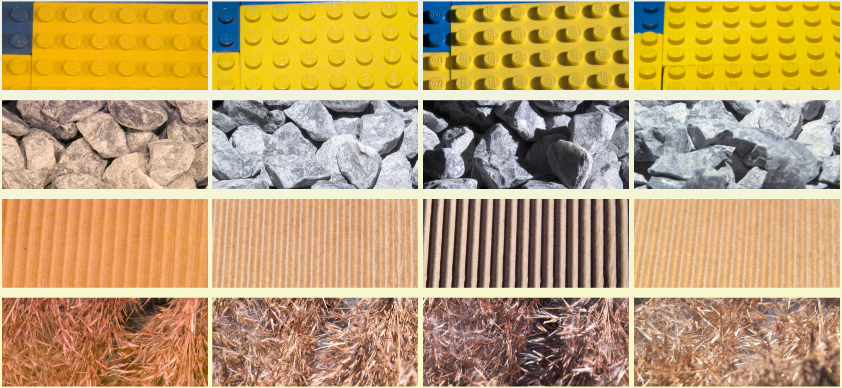

[Amsterdam Library of Textures (ALOT)]

Proposed Method Properties

Illumination variation:

- Illumination spectrum .... invariant
- Local intesity (cast shadows) ..... aprox. invariant
- Illumination direction .... robust

Unknown illumination conditions.

Single training image per material (texture).

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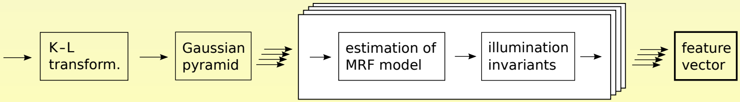
Algorithm

1. Karhunen-Loeve transformation (optinal)
2. Gaussian-downsampled pyramid with K levels
3. Markovian texture representation
4. Estimate of MRF model parameters
5. **Illumination invariants are derived from the model parameters**



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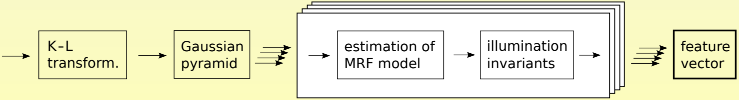


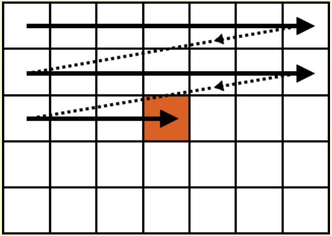
MRF-CAR Model

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

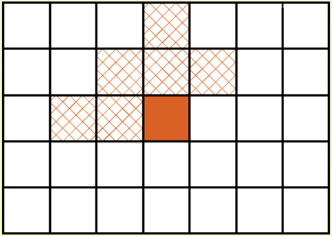
r, s	pixel multiindices, $r =$ (row, column)
Y_r	vector value (R, G, B) at texture position r
I_r	causal contextual neighbourhood with size η
A_s	**unknown parameter matrices**
ϵ_r	white noise with zero mean and unknown covariance matrix

Model Parameter Estimation

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



movement



neighbourhood I_r

Illumination Invariance

Two images Y, $\tilde{Y}$ of the same surface illuminated with different illumination 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

Illumination Invariants:

1. trace: $\mathrm{tr}\, A_s$ $\quad s \in I_r$
2. diagonals: $\nu_{s,j} = \mathrm{diag}(A_s)$ $\quad s \in I_r, \; j = 1, \ldots, C$

C	number of spectral planes ($C = 3$)
I_r	causal contextual neighbourhood

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

$Z_r = [Y_{r-s}^T : \forall s \in I_r]^T$		data vector,
$V_{zz} \approx \sum_r Z_r Z_r^T$		used in model parameter estimation,
λ		used in noise estimation

Thorough evaluation

Experiments:

- 4 textural databases, about 10 000 images
- 1-NN classification
- 1 – 6 training images per material

Acquisition conditions:

- Illumination spectrum .... tested
- Illumination azimuth and declination .... tested
- Acquisition device .... tested

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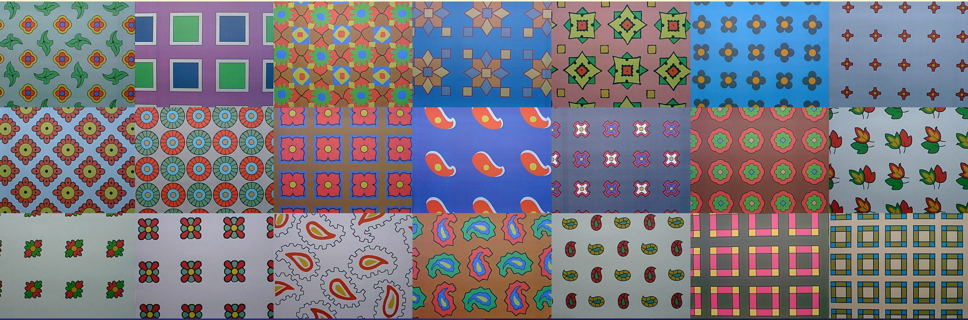
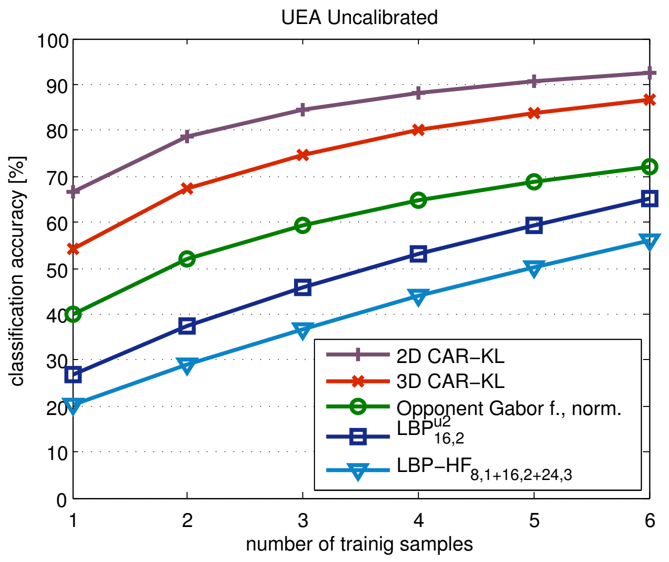
UEA Uncalibrated database

- 3 illumination spectra, 6 acquisition devices

- 28 materials



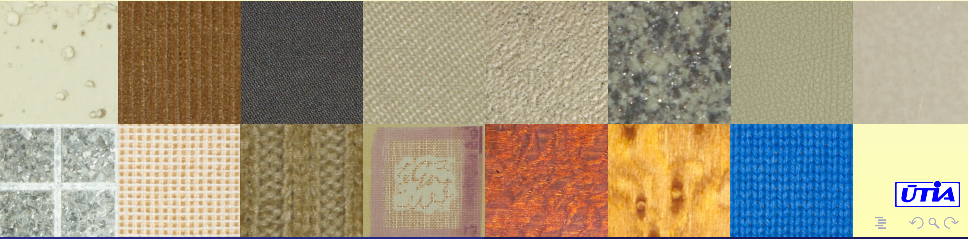
UEA Uncalibrated - Results



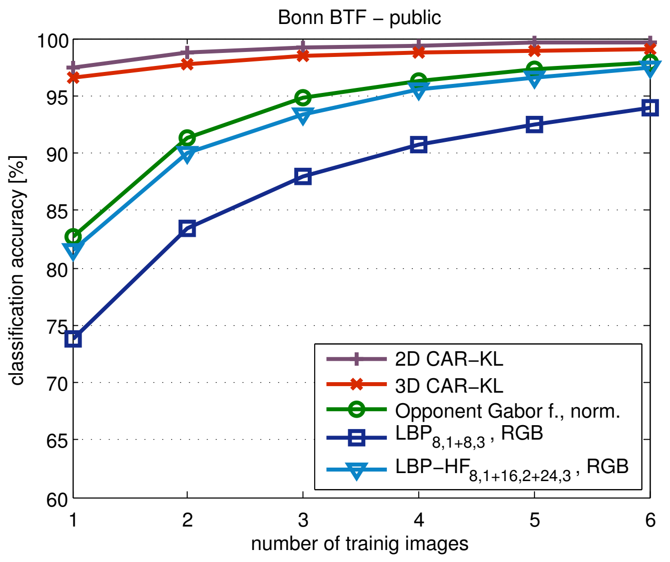
University of Bonn BTF Database

- 81 illumination directions
  declination $[0^\circ, \ldots, 75^\circ]$, azimuth $[0^\circ, \ldots, 360^\circ]$

- 15 materials



Bonn BTF – Results

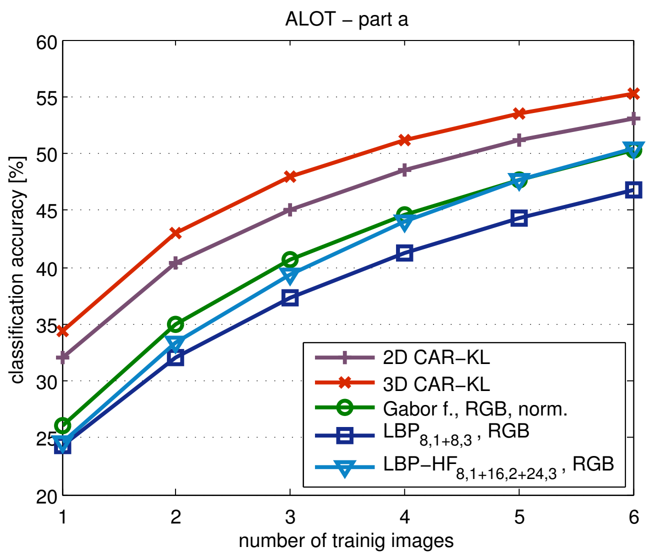


Amsterdam Library of Textures (ALOT)

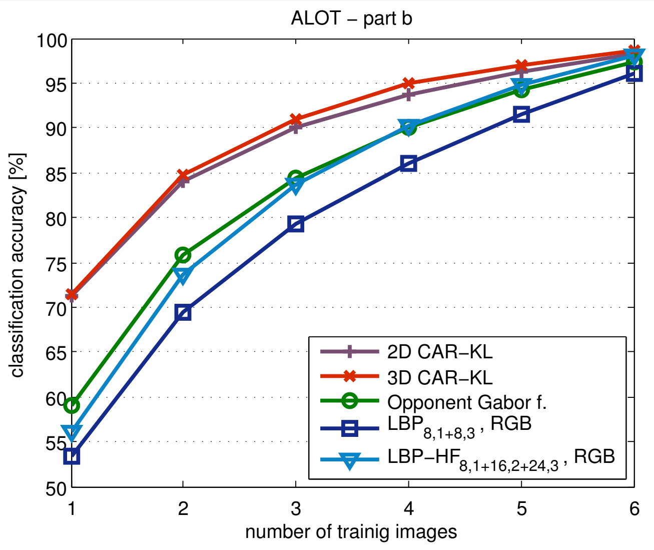
- 4 cameras, 6 illumination directions, 2 spectra

- high resolution RGB images (min 1536 $\times$ 660)
- **250** materials

ALOT - No Rotation Results



ALOT - Fixed Camera Position Results



Conclusion

Summary:

- Invariant to illumination spectrum and cast shadows
- Robust to illumination direction
- Illumination knowledge not needed
- Significant improvement over Gabor features, LBP

- Verified in thorough experiments

Future Plans:

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Demonstration

http://cbir.utia.cas.cz/

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Thank you for your attention

References

- Amsterdam Library of Textures ALOT.
  http://staff.science.uva.nl/~mark/ALOT/.
- University of Bonn BTF databse.
  http://btf.cs.uni-bonn.de.

- P. Vacha and M. Haindl.
  Texture Recognition using Robust Markovian Features. In *Proceedings MUSCLE Workshop 2011, Pisa, Italy*. (in press).