Query by Pictorial Example

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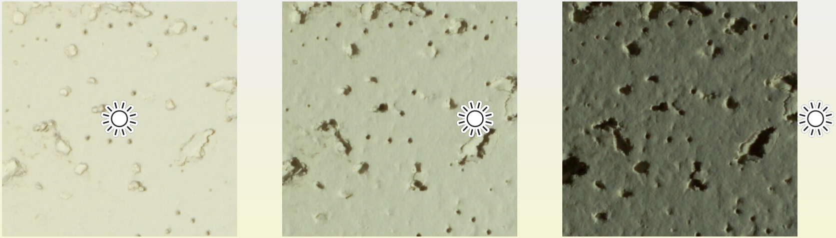
Real Scene – Appearance Variation

Material Appearance Variation



[University of Bonn BTF Database]

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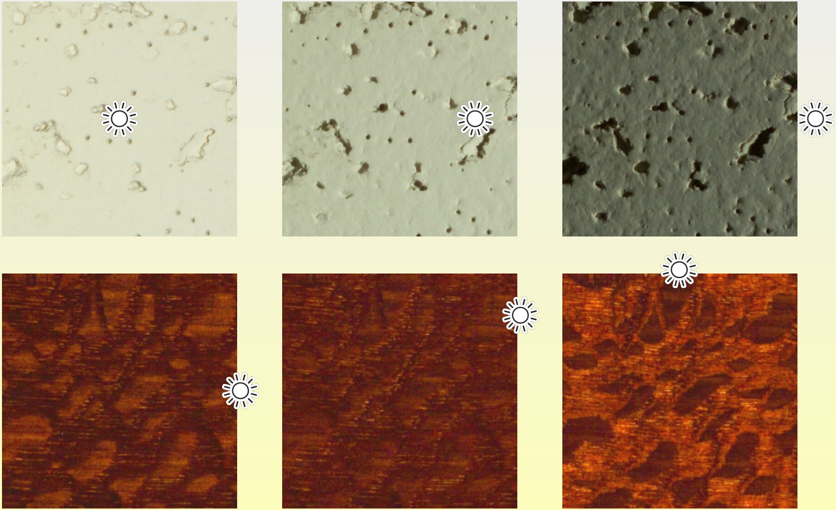

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Outline

Texture Recognition Algorithm

1. Gaussian-downsampled pyramid with K levels
2. Markovian texture representation
3. Estimate of parameters of Markov random field
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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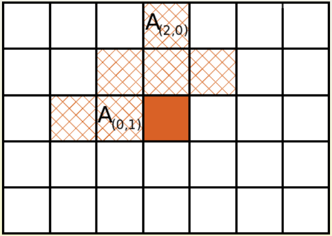
Causal AutoRegressive (CAR) Model

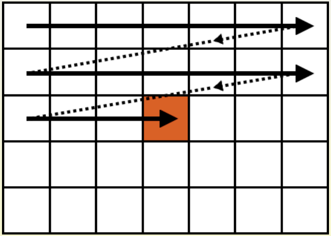
$$Y_r = \sum_{s \in I_r} A_s Y_{r-s} + \epsilon_r$$

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



shape of neighbourhood I_r

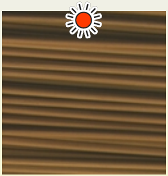
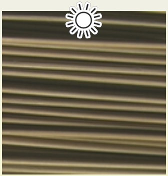
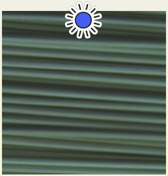


incremental estimation

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

Illumination Invariance

Same surface illuminated with different spectra:

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

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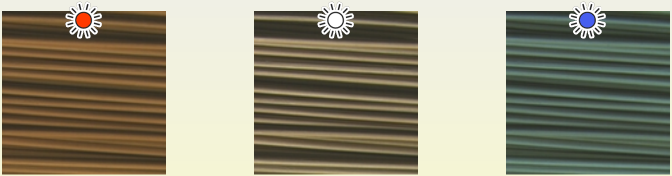

$$\breve{B}^{-1}\breve{A}_s\,\breve{B} \quad \approx \quad A_s \quad \approx \quad \tilde{B}^{-1}\tilde{A}_s\,\tilde{B}$$

Illumination Invariants:

1. trace: $\operatorname{tr} A_s$ $\qquad s \in I_r$
2. eigenvalues: $\nu_{s,j}$ of A_s $\qquad s \in I_r,\ \ j = 1, \ldots, C$

C is number of spectral planes

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}, V_{yy} model statistics
μ mean of vector Y_r

Illumination Invariants

6. $\beta_1 = \log\left(\frac{|t|}{|r|}|\lambda_r||\lambda_t|^{-1}\right)$

7. $\beta_2 = \log\left(\frac{|t|}{|r|}|V_{zz(r)}||V_{zz(t)}|^{-1}\right)$

8. $\beta_3 = \log\left(|V_{zz(r)}||\lambda_r|^{-\eta}\right)$

9. $\beta_4 = \log\left(|V_{zz(r)}||V_{yy(r)}|^{-\eta}\right)$

10. $\beta_5 = \mathrm{tr}\left\{V_{yy(r)}\lambda_r^{-1}\right\}$

11. utilising prediction probability $p(Y_r|Y^{(r-1)})$

12. utilising model probability $p(M|Y^{(r)})$

13. ...

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Proposed Method Properties

Illumination variation:

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

Unknown illumination conditions.

Single training image per material (texture).

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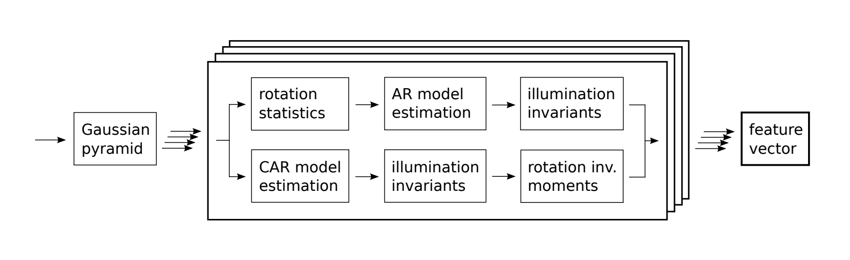
Rotation Invariance - Approaches

- First approach
  1. Rotation invariance
  2. Modelling
- Second approach
  1. Modelling
  2. Rotation invariance



Moments Invariants

Discrete moment of order $p + q$ of function f:

$$c_{pq}^{(f)} = \sum_{r_1} \sum_{r_2} (r_1 + ir_2)^p (r_1 - ir_2)^q f(r_1, r_2)$$

Set of moment invariants (even-order):

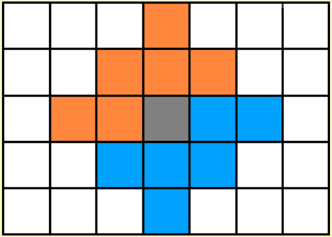
1. zeroth order: c_{00}
2. second order: c_{11} , $c_{20} c_{02}$
3. fourth order: c_{22} , $c_{40} c_{04}$, $c_{31} c_{13}$
4. mixed order: $\Re(c_{40} c_{02}^2)$, $\Re(c_{31} c_{02})$.
5. joint colour, second order: $c_{20}^{(\ell)} c_{02}^{(j)}$,

Combination with Illumination Invariants

The moment invariants are computed from features:

- traces tr A_s:

$$f_A(r_1, r_2) = \begin{cases} \operatorname{tr} A_{(r_1, r_2)} & (r_1, r_2) \in I_r^u \\ \operatorname{tr} A_{(-r_1, -r_2)} & (-r_1, -r_2) \in I_r^u \\ 0 & \text{otherwise} \end{cases}$$



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- each spectral plane of ν_j:

$$f_{\nu,j}(r_1, r_2) = \begin{cases} \nu_{(r_1, r_2),j} & (r_1, r_2) \in I_r^u \\ \nu_{(-r_1, -r_2),j} & (-r_1, -r_2) \in I_r^u \\ 0 & \text{otherwise} \end{cases}$$

Other illumination invariants are not associated with position in neighbourhood.

Outline

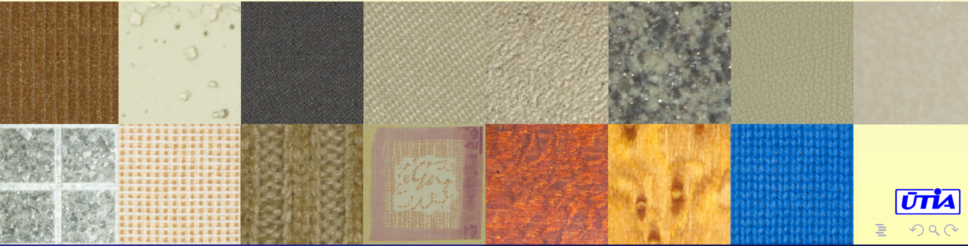
Bonn BTF Database

Textures:

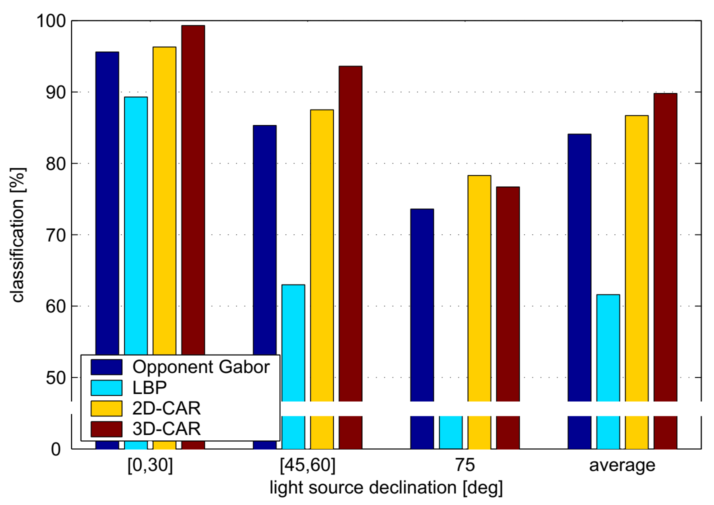
- 81 illumination directions
  declination $[0^\circ, \ldots, 75^\circ]$, azimuth $[0^\circ, \ldots, 360^\circ]$
- 15 materials

Training:

- Single training image per material



Results – Single Training Image

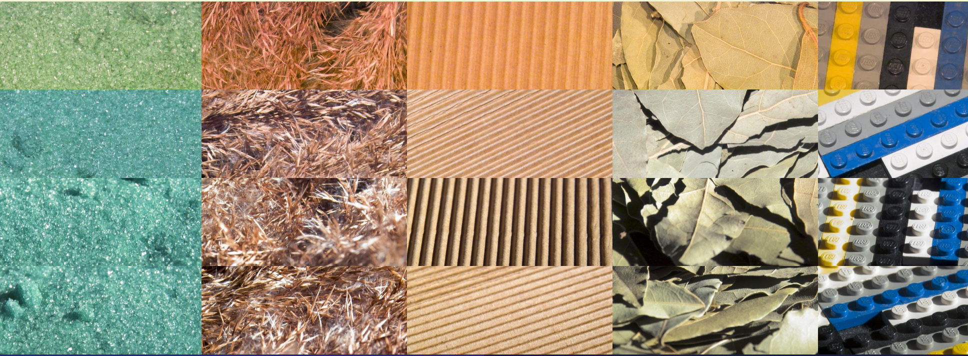


Training image fixed to the top illumination – angle 0°

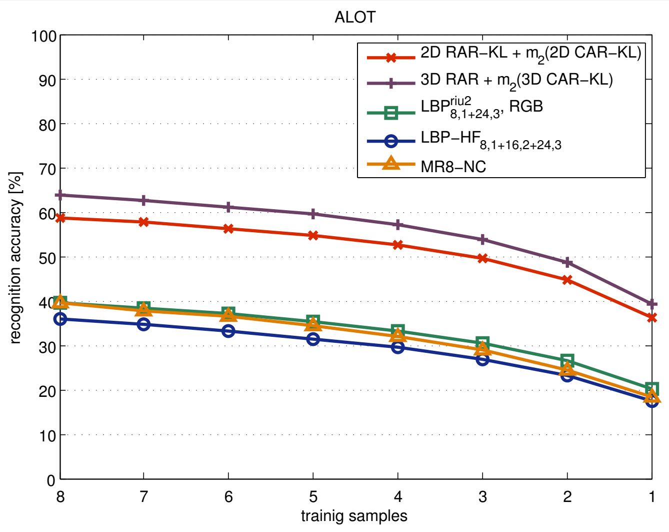
Amsterdam Library of Textures (ALOT)

Textures:

- high resolution RGB images (min 1536×660)
- 4 cameras, 6 illumination directions
  3 rotations, 1 additional illumination spectrum
- 250 materials

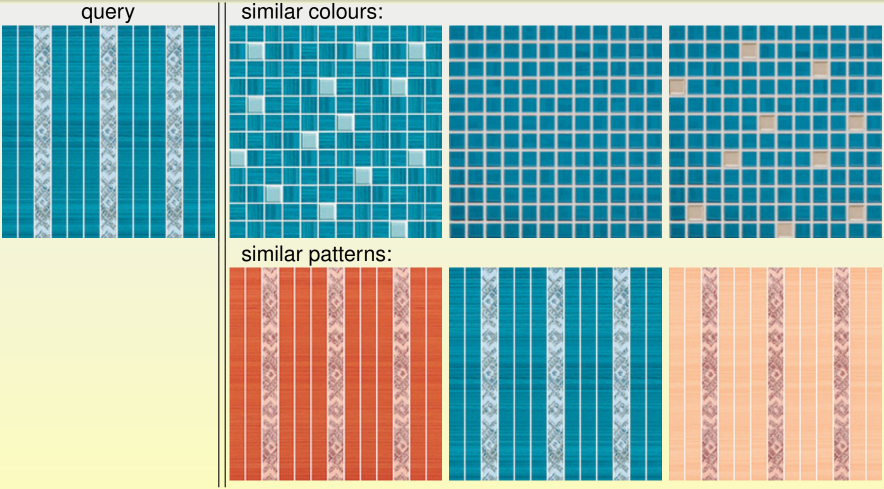


Results – ALOT



10^3 random samples of training images

Content-based Tile Retrieval System



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

- Psychophysical experiment: 76% considered very similar or similar

Applications

- **Illumination invariant texture segmentation**
  Improvement of most of segmentation criteria, including correct segmentation.

- **Texture compression optimization**
  Correlation of texture degradation descripton with human perception: **0.79**

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  Correct classification: **96%**

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Conclusion

Novel textural features:

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- Robust to illumination direction and Gaussian noise
- Robust to real material rotation

- No knowledge of acquisition conditions
- Single training image per material (for similar views)
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P. Vacha, M. Haindl, and T. Suk.
Colour and rotation invariant textural features based on Markov random fields.
Pattern Recognition Letters, vol. 32, pp. 771-779, April 2011.

Conclusion

Feature plans:

- Texture based image representation
- Robustness to scale and perspective projection
- Compound texture model
- Dynamic textures

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

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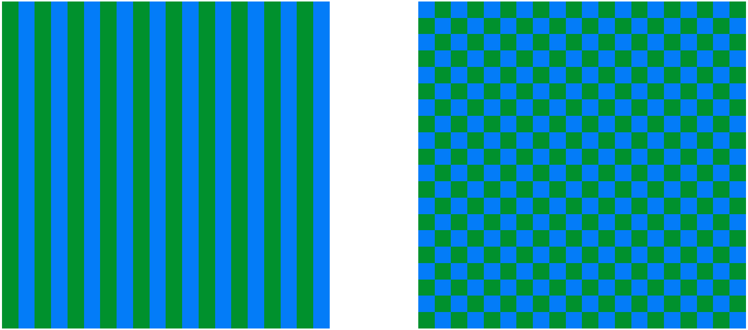
Thank you for your attention

Invalidity of Grey-scale Representation



Two different textures

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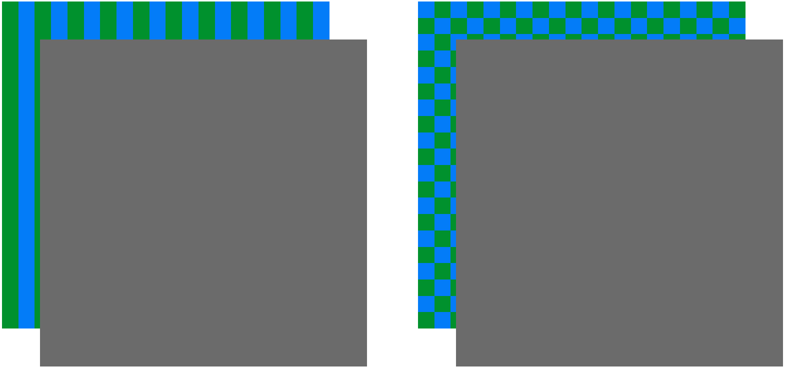

... and their grey-scale images.

References

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  Pattern Recognition Letters, 30:306–313, 2009.

References

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  Natural material recognition with illumination invariant textural features. In *Proc. of ICPR 2010, pp. 858-861*. IEEE, 2010.

References

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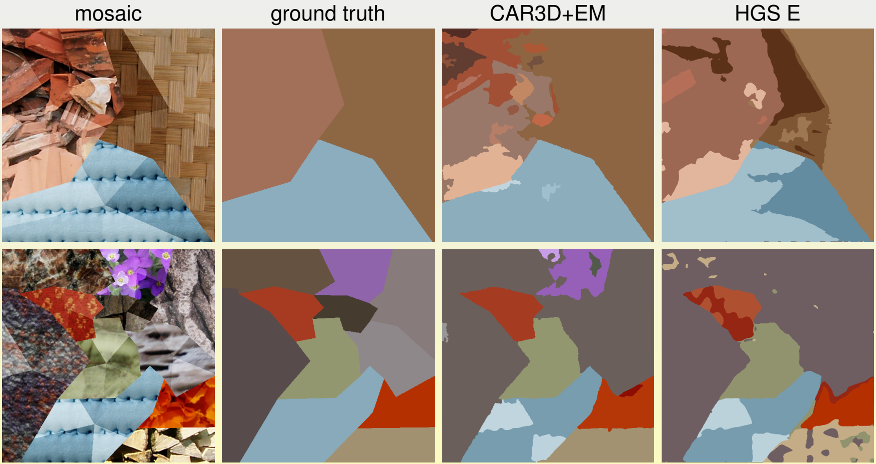
Illumination Invariant Texture Segmenter



[Haindl, Mikes, and Vacha, 2009] `http://mosaic.utia.cas.cz`

- Four times better in correct segmentation criterion

Model Parameter Estimation I

$$\begin{aligned} Z_r &= [Y_{r-s}^T : \forall s \in I_r]^T && \text{data vector} \\ \hat{\gamma} &= [A_s : \forall s \in I_r] && \text{parameter matrices estimate} \end{aligned}$$

Bayesian estimate from the process history $Y_1 \cdots Y_{t-1}$ **,** $Z_1 \cdots Z_{t-1}$ **:**

$$\hat{\gamma}_t \approx \left(\sum_r^{t-1} Z_r Z_r^T \right)^{-1} \left(\sum_r^{t-1} Z_r Y_r^T \right) \approx \left(V_{zz,(t-1)} \right)^{-1} V_{zy,(t-1)}$$

$V_{yy,(t-1)} \approx \sum_r^{t-1} Y_r Y_r^T$ used in noise estimation,

λ_t used in noise estimation

Model Parameter Estimation II

$$\lambda_{t-1} = V_{yy(t-1)} - V_{zy(t-1)}^T V_{zz(t-1)}^{-1} V_{zy(t-1)}$$

$$\begin{aligned} FC_a(T,S) = m - \Bigg\{ & \sum_{\ell=1}^{m} \min \left\{ \tau(f_\ell^{(T)}), \tau(f_\ell^{(S)}) \right\} \\ & - a \sum_{\ell=1}^{m} \left| \tau(f_\ell^{(T)}) - \tau(f_\ell^{(S)}) \right| \Bigg\} \end{aligned} ,$$

$$\tau(f_\ell) = \left(1 + \exp\left(- \frac{f_\ell - \mu(f_\ell)}{\sigma(f_\ell)} \right) \right)^{-1} ,$$

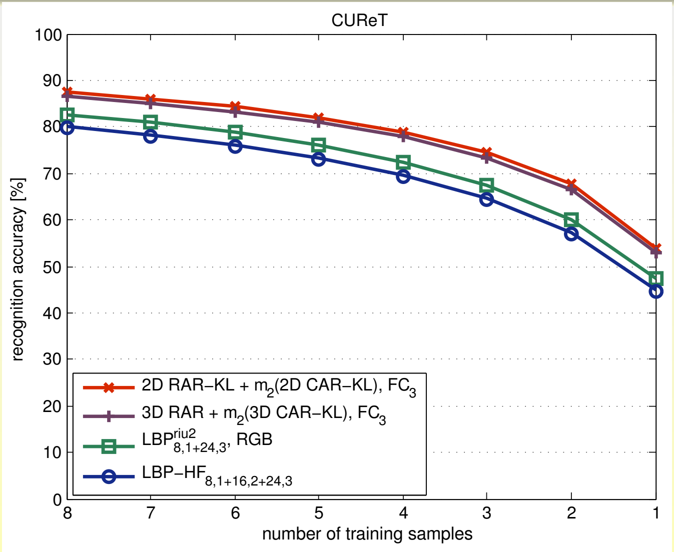
Experiments - Setups

- **Texture databases:**

database	Outex	Bonn BTF	CUReT	ALOT	KTH-TIPS2
illum. spectrum	$+$	$-$	$-$	$+$	$+$
illum. direction	$-$	$+$	$+$	$+$	$+$
view. azimuth	$-$	$-$	$+$	$-/+$	$-$
view. declination	$-$	$-$	$+$	$+$	$-$
image size	512/128	256	200	1536	200
no. materials	318/68	15/10	61	200/250	11

- **Classificator:**
  Nearest neighbour

Results – CUReT



10^3 random samples of training images