Natural Material Recognition with Illumination Invariant Textural Features

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ICPR 2010, Istanbul

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Proposed method

Illumination invariance

Results

Conclusion

References

Real Scene – Illumination Dependency



Vácha, Haindl Material Recognition

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Amsterdam Library of Textures (ALOT)



http://staff.science.uva.nl/~mark/ALOT/

[Burghouts and Geusebroek, 2009]



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Proposed Method Properties

Illumination variation:

Illumination spectruminvariant
 Local intesity (cast shadows) aprox. invariant
 Illumination directionrobust

Unknown illumination conditions. **Single training image per material (texture).**



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1. Gaussian-downsampled 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



Illumination invariance

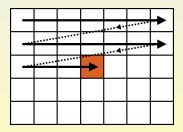
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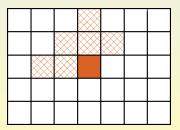
References

Model Parameter Estimation

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



movement



neighbourhood I_r

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Model Parameter Estimation

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

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

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

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

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 $V_{yy,(t-1)} \approx \sum_{r}^{t-1} Y_r Y_r^T$ used in noise estimation, λ_t used in noise estimation Two images Y, \tilde{Y} of the same surface illuminated with different illumination spectra:

 $A_s pprox B^{-1} ilde{A_s} B$

Illumination Invariants:

- 1. trace: tr A_s
- 2. eigenvalues: $\nu_{s,j}$ of A_s

 $s \in I_r$ $s \in I_r, j = 1, \dots, C$

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C is number of spectral planes

3.
$$\beta_1 = \log\left(\frac{1}{r-t}|\lambda_r||\lambda_t|^{-1}\right)$$

4.
$$\beta_2 = \log \left(\frac{1}{r-t} |V_{zz(r)}| |V_{zz(t)}|^{-1} \right)$$

5.
$$\beta_3 = \log\left(|V_{zz(r)}||\lambda_r|^{-\eta}\right)$$

$$\textbf{6.} \quad \beta_4 = \mathsf{tr}\left\{V_{yy(r)}\lambda_r^{-1}\right\}$$

9. ...

- 7. utilising prediction probability $p(Y_r|Y^{(r-1)})$
- 8. utilising model probability $p(M|Y^{(r)})$



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Experimental Setup

Textures:

- Amsterdam Library of Textures (ALOT)
- 4 cameras, 6 illumination directions,
 - 1 additional illumination with different spectrum
- high resolution RGB images (min 1536 × 660)
- 250 materials



Experimental Setup

Tests:

- [Burghouts and Geusebroek, 2009] without rotation, separate training and test sets (6 + 6 images), perspective projection
- Single training image per material (14 images per material) no perspective projection

Classification:

- Nearest neighbour classification
- 10³ random samples of training images



Results

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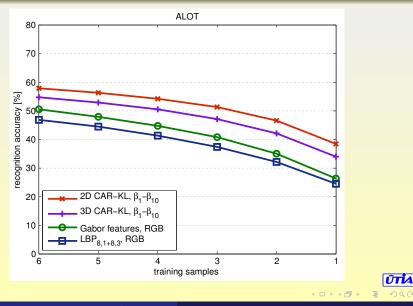


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Results - [BG, 2009] Without Rotation



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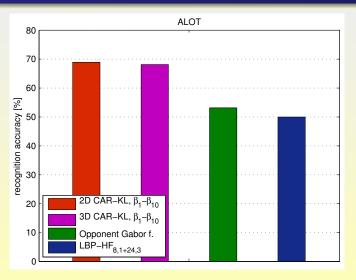
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Results – Single Training Images





Summary:

- Invariant to illumination spectrum and cast shadows
- Robust to illumination direction
- Illumination knowledge not needed
- Single training image per material (for limited viewpoint variation)
- 9-16% improvement over Gabor features, LBP

Future Plans: Rotation invariance Integration to a CBIR system



Summary:

- Invariant to illumination spectrum and cast shadows
- Robust to illumination direction
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Future Plans:

- Rotation invariance
- Integration to a CBIR system

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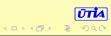
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Demonstration

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

{vacha,haindl}@utia.cz

Thank you for your attention



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- G. J. Burghouts and J. M. Geusebroek. Material-specific adaptation of color invariant features. *Pattern Recognition Letters*, 30:306–313, 2009.
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