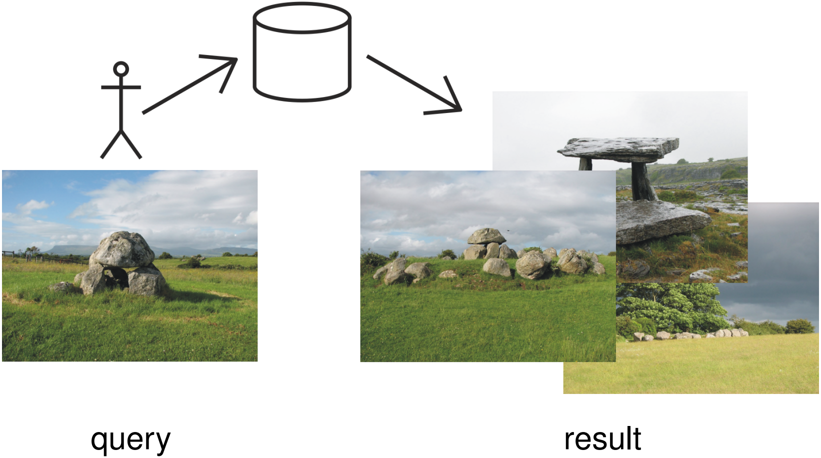
Illumination Invariant Texture Retrieval

Pavel Vácha, Michal Haindl

Institute of Information Theory and Automation,
AS CR

2nd International Workshop on
Data - Algorithms - Decision Making
2006

Image retrieval



Outline

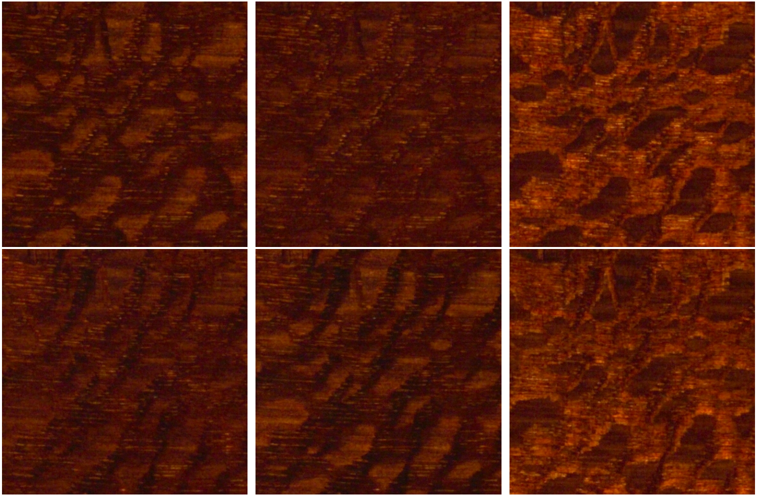
What is a texture?

Texture is homogeneous and translation invariant

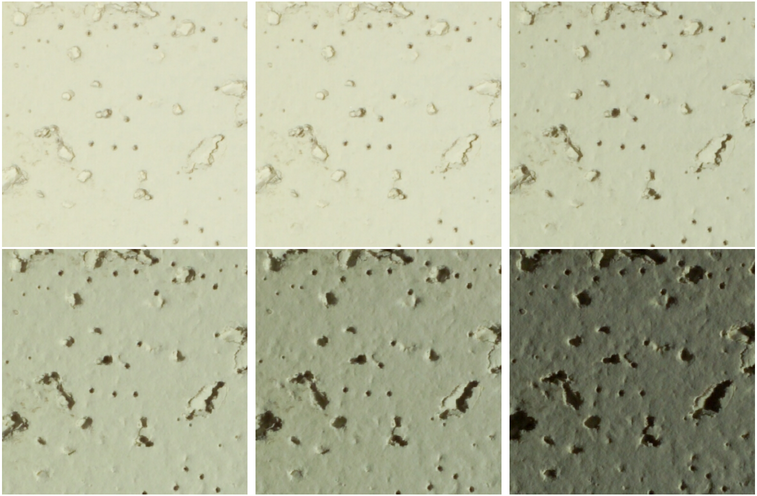
Possible texture definitions:

- Realisation of random field
- Texture elements placed according to rules
- Information that permits the human eye to differentiate between image regions.

Examples of textures – azimuth



Examples of textures – declination



Illumination

Illumination conditions are unknown.

Types of illumination variations:

- Illumination brightness
- Illumination direction
- Illumination spectrum

Illumination

Illumination conditions are unknown.

Types of illumination variations: our method

- Illumination brightness .... invariant
- Illumination direction .... robust
- Illumination spectrum .... not tested

Proposed method

1. Grey scale image
2. Image gradients
3. Gaussian pyramid with K levels
4. Modelling by a Markov random field (MRF) model
5. Estimated MRF model parameters are features
6. Feature vectors are compared in L_1 norm

CAR model

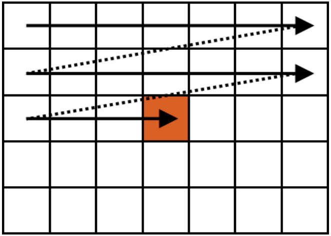
$$Y_r = \gamma Z_r + \epsilon_r$$

$r \quad = \text{(row, column)}$ pixel multiindex
$Z_r = [Y_{r-i}^T : \forall i \in I_r]^T$ data vector
I_r contextual causal or unilateral neighbourhood

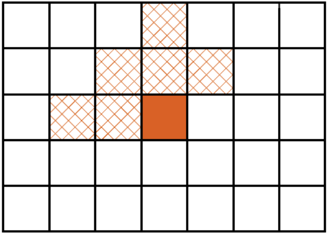
$\gamma \quad = [A_1, \ldots, A_\eta]$ unknown parameter matrix with diagonal matrices A_i
ϵ_r white noise with zero mean and unknown covariance matrix

CAR model – parameter estimation

- Analytical recursive Bayesian estimation of γ



movement



neigbourhood

GMRF model

Local condition density is Gaussian.
I_r non-causal symmetrical neighbour index set

The GMRF model has the form of CAR model with the following noise correlation (diagonal σ):

$$E\{\epsilon_{r,i}\epsilon_{r-s,j}\} = \begin{cases} \sigma_j^2 & \text{if } (s) = (0,0) \text{ and } i = j, \\ -\sigma_j^2 a_j^s & \text{if } (s) \in I_r^j \text{ and } i = j, \\ 0 & \text{otherwise.} \end{cases}$$

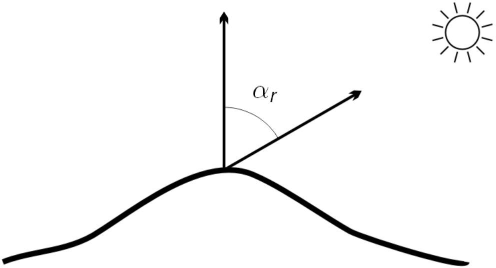
$\sigma_j, a_j^s \; \forall s \in I_r^j$ unknown parameters.

- Pseudo-likelihood estimation of γ.

Illumination model

Lambertian law:

$$Y_r = \rho_r \cos \alpha_r L$$



Invariance of the method

Two images Y, Y' of the same Lambertian surface illuminated with different illumination brightnesses:

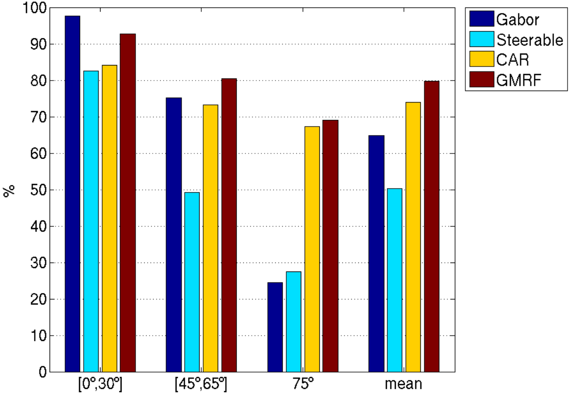
$$Y_r = cY'_r$$

$$\begin{aligned} Y_r &= \gamma Z_r + \epsilon_r \\ cY'_r &= \gamma' c Z'_r + \epsilon'_r \end{aligned}$$

$$\gamma \approx \gamma'$$

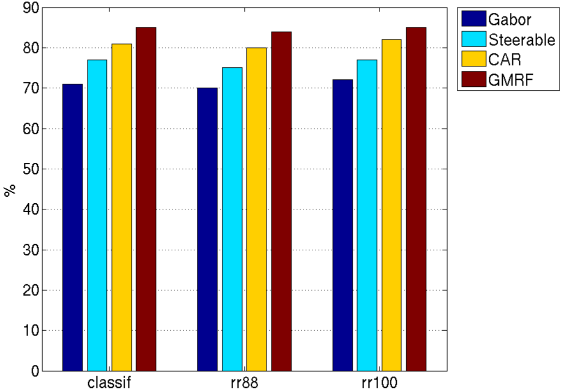
- Feature vector: $[\gamma^{(k)}]$, $k = 1 \ldots K$, k is Gaussian pyramid level.

Results – declination angle



Classification performance [%]. Class etalons ware top lighted images, the others were classified.

Results – all textures



Estimated probability of correct classification and recall rate (rr_n) for n textures retrieved [%].

Conclusion

- Single training image per class.
- Invariant to illumination brightness
- Robust to illumination direction
- Illumination direction knowledge not needed.

Conclusion

- Single training image per class.
- Invariant to illumination brightness
- Robust to illumination direction
- Illumination direction knowledge not needed.

- Average improvement 4 – 14% to Gabor / Steerable pyramid based methods.
- Two times faster than the Gabor filter method.
- Recursive analytical solution (CAR model).

References

- M. Haindl, P. Vácha
  Illumination Invariant Texture Retrieval
  in: *Proc. of the 18th International Conference on Pattern Recognition (ICPR'06)*, pages 276–279, Hong Kong, August 2006.

- J. Meseth and G. Müller and R. Klein,
  Preserving realism in real-time rendering,
  in: *OpenGL Symposium*, pp., 89–96, 2003.

Results – declination angle

method	$[0^o; 30^o]$	$[45^o; 65^o]$	75^o	mean
Gabor	97.6	75.2	24.4	64.9
Steerable	82.5	49.2	27.4	50.2
CAR	84.1	73.3	67.2	73.9
GMRF	92.8	80.5	69.0	79.8

Classification performance [%]. Class etalons are top lighted images, the others were classified.

Results – all texture

method	$P(correct)$	rr_{88}	rr_{100}
Gabor	71	70	72
Steerable	77	75	77
CAR	81	80	82
GMRF	85	84	85

Estimated probability of correct classification and recall rate (rr_n) for n textures retrieved [%].

CAR model - parameter estimation I

The task consists in finding the conditional parameters density $p(\gamma \mid Y^{(t-1)})$ given the known process history $Y^{(t-1)} = \{Y_{t-1}, Y_{t-2}, \ldots, Y_1, Z_t, Z_{t-1}, \ldots, Z_1\}$ and taking its conditional mean as the textural feature representation. Assuming normality of the white noise component ϵ_t, conditional independence between pixels and the normal-Wishart parameter prior, we have shown that the conditional mean value is:

$$E[\gamma \mid Y^{(t-1)}] = \hat{\gamma}_{t-1} \quad . \tag{1}$$

CAR model - parameter estimation II

The following notation is used:

$$\hat{\gamma}_{t-1} = V_{zz(t-1)}^{-1} V_{zy(t-1)} \ ,$$

$$V_{t-1} = \tilde{V}_{t-1} + V_0 \ ,$$

$$\tilde{V}_{t-1} = \begin{pmatrix} \sum_{u=1}^{t-1} Y_u Y_u^T & \sum_{u=1}^{t-1} Z_u Y_u^T \\ \sum_{u=1}^{t-1} Z_u Y_u^T & \sum_{u=1}^{t-1} Z_u Z_u^T \end{pmatrix} = \begin{pmatrix} \tilde{V}_{yy(t-1)} & \tilde{V}_{zy(t-1)}^T \\ \tilde{V}_{zy(t-1)} & \tilde{V}_{zz(t-1)} \end{pmatrix}$$

and V_0 is a positive definite matrix. We assume slowly changing parameters, consequently these equations were modified using a constant exponential "forgetting factor" α to allow parameter adaptation.

CAR model - parameter estimation III

It is easy to check also the validity of the following recursive parameter estimator:

$$\hat{\gamma}_t = \hat{\gamma}_{t-1} + \frac{V_{zz(t-1)}^{-1} Z_t (Y_t - \hat{\gamma}_{t-1}^T Z_t)^T}{(\alpha^2 + Z_t^T V_{zz(t-1)}^{-1} Z_t)} \quad . \tag{2}$$

The solution uses the following notations:

$$\begin{aligned} \psi(t) &= \alpha^2 \psi(t-1) + 1 \quad , & (3) \\ \lambda_{t-1} &= V_{yy(t-1)} - V_{zy(t-1)}^T V_{zz(t-1)}^{-1} V_{zy(t-1)} \quad . & (4) \end{aligned}$$

The determinant $|V_{zz(t)}|$ as well as λ_t can be evaluated recursively too.