Illumination Invariant Texture Retrieval

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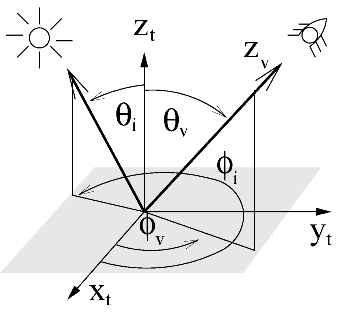
Abstract

Two fast illumination invariant image retrieval methods for scenes comprising textured objects with variable illumination are introduced. Both methods are based on texture gradient modelled by efficient set of random field models. We developed the illumination insensitive measures for textured images representation and compared them favorably with steerable pyramid and Gabor features in the illumination invariant BTF texture recognition.

Problem formulation



Illumination invariant texture retrieval using single training image per class with unknown illumination direction. Textures from the University of Bonn BTF database (81 different illuminations for a fixed view per texture).

Proposed Solution

- Multiscale texture gradient based on MRF type of BTF texture representations:
  1. CAR texture representation,
  2. GMRF texture representation.

Texture Gradient

kth Scale Texture Gradient

$$Y_r^{(k)} = \left[\frac{\partial Y_r^{(k)}}{\partial r_1}, \frac{\partial Y_r^{(k)}}{\partial r_2}\right]^T$$

Multiscale decomposition - k levels of the image (Y) Gaussian pyramid.

Texture gradient is reasonable insensitive to illumination direction changes.

Gradient parametric representation:
$\Theta = [\gamma^{(k)}\ \forall k]$ where $\gamma^{(k)}$ is the corresponding k-th scale factor model parameter matrix.

CAR Factor Model

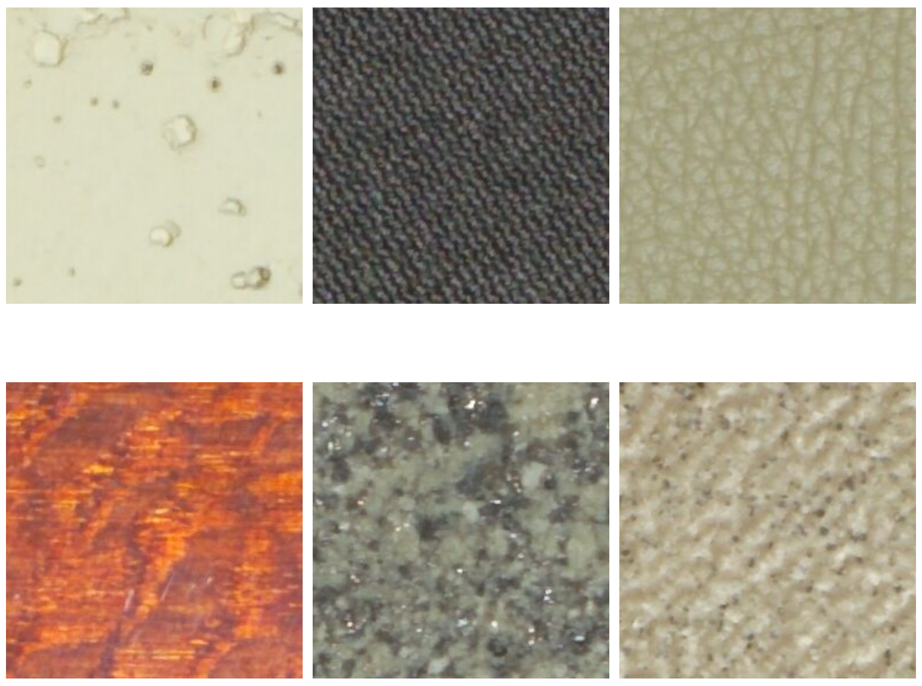
$$Y_r = \gamma Z_r + \epsilon_r$$

$\gamma = [A_1, \ldots, A_\eta]$ unknown parameter matrix
A_i diagonal matrices
$Z_r = [Y_{r-i}^T : \forall i \in I_r]^T$ data vector

I_r contextual causal or unilateral neighbour index set
$r = (r_1, r_2)$ multi-index (row, column)
ϵ_r white noise with zero mean and unknown covariance matrix

Analytical recursive Bayesian estimation of γ.

- BTF textures used in the retrieval experiments



GMRF Factor model

Local condition density is Gaussian:

$$p(Y_r | Y_s\ \forall s \in I_r) = \frac{\exp\left\{-\frac{1}{2}(Y_r - \gamma Z_r)^T \Sigma^{-1} (Y_r - \gamma Z_r)\right\}}{2\pi |\Sigma|^{\frac{1}{2}}},$$

I_r non-causal symmetrical neighbour index set

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

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

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

Pseudo-likelihood estimation of γ.

The Retrieval Algorithm

- Analysis
  1. Factorize the texture into a multiscale representation using the Gaussian pyramid.
  2. Find the parametric repesentation of the multiscale texture gradient for each texture.
- Retrieval
  1. Find the n nearest textures to a given target texture based on the L_1 norm
     $j^* = \arg\min_j |\Theta - \Theta_j|$.

Experiments

BTF textures are from the University of Bonn [?] and contain BTF colour measurements such as foil, lacquered wood, floor-tile, floor-plastic, glazed tile, fabric or ceiling panel textures. Each BTF material sample is measured in 81 illumination angles and it has the resolution 512×512.

Classification performance comparison in [%] for the BTF test set. Class etalons are top ligthed images, the others are classified.

method	$< 0^o; 30^o >$	$< 45^o; 65^o >$	75^o	aver.
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

Estimated probability of correct classification and recall rate (rr_n) for n textures retrieved. Classification of samples 10^5, retrieval of every image.

method	Gabor	Steerable	CAR	GMRF
$P(correct)$	0.71	0.77	0.81	0.85
rr_{88}	0.70	0.75	0.80	0.84
rr_{100}	0.72	0.77	0.82	0.85

Conclusions

- ⊕ Illumination invariance.
- ⊕ Single training image per class.
- ⊕ 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).

ICPR 2006, Hong Kong, China