Colour Texture Retrieval Based on Illumination Invariant MRF Features

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Outline

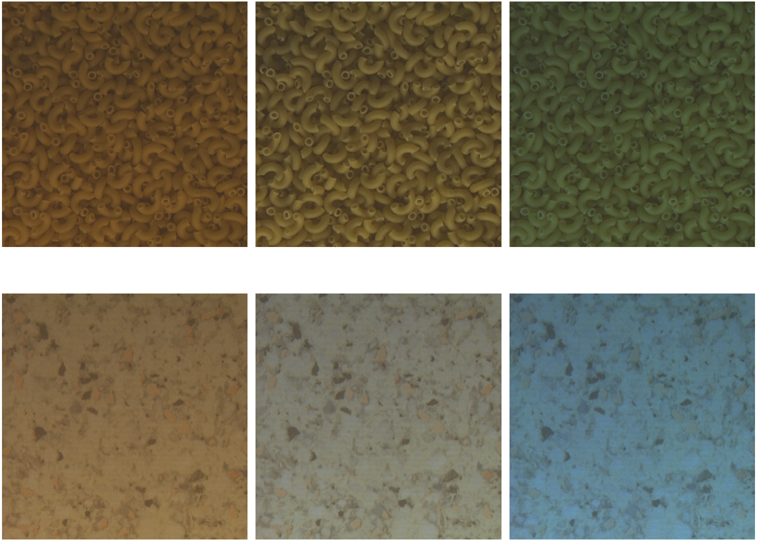
What is a texture retrieval?

Image retrieval returns images from the database that are similar to the query

Texture is homogeneous and translation invariant
Possible texture definitions:

- Realisation of random field
- Texture elements placed according to rules

Effects of illumination - Outex



Illumination model

$$Y_{r,j} = \int_{\omega} E(\lambda)\, S(r,\lambda)\, R_j(\lambda)\, d\lambda$$

$Y_{r,j}$	value of the $j-$th sensor at position r, pixel multiindex $r = $ (row, column)
$E(\lambda)$	illumination spectral distribution
$S(r,\lambda)$	Lambertian reflectance coefficient
$R_j(\lambda)$	response function of the $j-$th sensor
ω	visible spectrum

Approximation by fixed basis

$$S(r,\lambda) = \sum_{c=1}^{C} d_c\, s_c(\lambda)$$

Two images $\tilde{Y}$, Y with different illumination are related by $C \times C$ matrix[Finlayson]:

$$\tilde{Y}_r = B\, Y_r \qquad \forall r$$

Assumptions:

- illumination and view point are fixed
- C sensors available

Illumination invariance

Proof conditions:

- arbitraty changes of illumination spectrum
- unknown illumination spectrum

- single illumination with fixed direction

Test on Outex database:

- three illumination sources: horizon sunlight, incandescent CIE A, fluorescentTL84
- 318 textures

Texture representation

Method:

1. Gaussian pyramid with K levels
2. Modelling by a Markov random field (MRF) model, one or two directions
3. Illumination invariants based on MRF model parameters
4. Feature vectors are compared in L_1 norm

CAR model

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

I_r	contextual causal or unilateral neighbourhood
A_s	unknown parameter matrices
ϵ_r	white noise with zero mean and unknown covariance matrix

$Z_r = [Y_{r-s}^T : \forall s \in I_r]^T$ data vector

$\gamma = [A_1, \ldots, A_\eta]$

- matrices A_s are diagonal in 2D CAR model

CAR model – parameter estimation

Analytical Bayesian estimation of γ:

$$
\begin{aligned}
\hat{\gamma}_{t-1}^T &= V_{zz(t-1)}^{-1} V_{zy(t-1)} \quad , \\
V_{t-1} &= \tilde{V}_{t-1} + V_0 \quad , \\
\tilde{V}_{t-1} &= \begin{pmatrix} \sum_{u=1}^{t-1} Y_u {Y_u}^T & \sum_{u=1}^{t-1} Y_u {Z_u}^T \\ \sum_{u=1}^{t-1} Z_u {Y_u}^T & \sum_{u=1}^{t-1} Z_u {Z_u}^T \end{pmatrix} \\
&= \begin{pmatrix} \tilde{V}_{yy(t-1)} & \tilde{V}_{zy(t-1)}^T \\ \tilde{V}_{zy(t-1)} & \tilde{V}_{zz(t-1)} \end{pmatrix} \quad , \\
\lambda_{t-1} &= V_{yy(t-1)} - V_{zy(t-1)}^T V_{zz(t-1)}^{-1} V_{zy(t-1)}
\end{aligned}
$$

V_0 is a positive definite matrix.

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 invariant features

Two images $Y, \tilde{Y}$ of the same texture illuminated with different spectra:

$$Y_r = B\tilde{Y}_r$$

$$
\begin{aligned}
Y_r &= \sum_{s \in I_r} A_s Y_{r-s} + \epsilon_r \\
B\tilde{Y}_r &= \sum_{s \in I_r} \tilde{A}_s B \tilde{Y}_{r-s} + \tilde{\epsilon}_r
\end{aligned}
$$

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

Illumination invariant features

Both models:

1. trace: $\operatorname{tr} A_m, \; m = 1, \ldots, \eta K$
2. eigenvalues: $\nu_{m,j}$ of $A_m, \; m = 1, \ldots, \eta K, \; j = 1, \ldots, C$

CAR model:

1. α_1: $1 + Z_r^T V_{x(r-1)}^{-1} Z_r$,
2. α_2: $\sqrt{\sum_r (Y_r - \hat{\gamma} Z_r)^T \lambda^{-1} (Y_r - \hat{\gamma} Z_r)}$,
3. α_3: $\sqrt{\sum_r (Y_r - \mu)^T \lambda^{-1} (Y_r - \mu)}$,
   μ is the mean value of vector Y_r,

Illumination invariant features

GMRF model with centered $Y_{r,j}$:

1. α_4: $\sqrt{\sum_r \hat{\sigma}_j^{-2} \left(Y_{r,j} - \hat{\gamma}_j Z_{r,j}\right)^2}$,
2. α_5: $\sqrt{\sum_r \hat{\sigma}_j^{-2} \left(Y_{r,j}\right)^2}$

Results – retrieval recall rate

	added noise σ			
method	0	2	4	8
Gabor f., grey img, norm.	53.4	58.1	58.7	56.1
Opponent Gabor f., norm.	46.9	45.0	40.9	37.8
Steerable pyramid, norm.	41.2	41.0	40.5	39.4
$\text{LBP}_{8,1+8,3}$, grey img.	**83.1**	**66.0**	**56.0**	**50.3**
GMRF-KL, $\alpha_4\alpha_5$	82.7	78.2	70.1	56.5
2CAR-KL 2x, $\alpha_1\alpha_2\alpha_3$	**89.2**	**86.3**	**80.5**	**68.7**
3CAR 2x, $\alpha_1\alpha_2\alpha_3$	**85.1**	**82.6**	**77.5**	**66.5**
2CAR-KL 2x, $\alpha_1\alpha_2\alpha_3$, $L_{1\sigma}$	**94.2**	92.9	89.2	81.7
3CAR-KL 2x, $\alpha_1\alpha_2\alpha_3$, $L_{1\sigma}$	90.3	88.3	81.8	69.2

Results – Outex classification test

	added noise σ			
method	0	2	4	8
Gabor f., grey img, norm.	54.5	61.3	63.3	62.9
Opponent Gabor f., norm.	56.7	55.8	54.3	47.9
Steerable pyramid, norm.	45.5	45.4	46.8	47.2
$LBP_{8,1+8,3}$, grey img.	**71.6**	**62.2**	**54.6**	**38.6**
GMRF-KL, $\alpha_4\alpha_5$	61.3	60.2	57.1	49.2
2CAR-KL 2x, $\alpha_1\alpha_2\alpha_3$	**67.5**	**65.2**	**61.8**	**56.4**
3CAR 2x, $\alpha_1\alpha_2\alpha_3$	**61.5**	**59.0**	**57.0**	**50.7**
2CAR-KL 2x, $\alpha_1\alpha_2\alpha_3$, $L_{1\sigma}$	**64.0**	63.4	63.4	57.9
3CAR-KL 2x, $\alpha_1\alpha_2\alpha_3$, $L_{1\sigma}$	58.5	57.6	52.7	46.3

Conclusion

- Single training image per class.
- Invariant to illumination spectrum

Conclusion

- Single training image per class.
- Invariant to illumination spectrum

- Robust to added noise
- Two times faster than the Gabor filter method.
- Recursive analytical solution (CAR model).

References

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  Outex - new framework for empirical evaluation of texture analysis algorithms,
  in: *Proc. of the 16th International Conference on Pattern Recognition (ICPR'02)*, pp., 701–706, August 2002.

References

- G. D. Finlayson
  Coefficient color constancy
  PhD thesis, Simon Fraser University, 1995.

Size of feature vectors

	experiment	
method	1	2
Gabor f.	144	144
Gabor f., grey img.	48	48
Opponent Gabor f.	**252**	**252**
Steerable pyramid	2904	2904
$LBP_{8,1+8,3}$, grey img.	**512**	**512**
GMRF-KL, $\alpha_4\alpha_5$	192	48
2CAR-KL 2x, $\alpha_1\alpha_2\alpha_3$	408	108
3CAR 2x, $\alpha_1\alpha_2\alpha_3$	360	96

GMRF model – parameter estimation

$$\hat{\gamma}_j^T = [a_{s,j} \quad \forall s \in I_r]^T$$

$$= \left[\sum_{\forall s \in I} Z_{s,j} Z_{s,j}^T\right]^{-1} \sum_{\forall s \in I} Z_{s,j} Y_{s,j}$$

$$\hat{\sigma}_j^2 = \frac{1}{|I|} \sum_{\forall s \in I} (Y_{r,j} - \hat{\gamma}_j Z_{r,j})^2$$