Results – Top Training Image

method	$[0°, 30°]$	$[45°, 65°]$	$75°$	avg.
Gabor features	96.3	71.4	28.9	64.2
Opponent Gabor	**95.6**	83.9	50.0	76.4
Opponent Gabor, nm.	**95.6**	85.3	73.6	**84.1**
$LBP_{8,1+8,3}$, grey	86.3	57.4	38.3	58.2
$LBP^{u}_{16,2}$, grey	79.3	50.7	34.7	52.3
$LBP_{8,1+8,3}$	**89.3**	63.0	38.6	**61.6**
$LBP^{riu}_{16,2}$	84.4	44.6	31.9	49.8
2D CAR-KL, L_1	96.3	87.5	78.3	86.7
3D CAR	**97.8**	89.6	75.6	87.2
GMRF-KL	95.9	82.6	65.3	80.4
2D CAR-KL, FC_3	**97.8**	90.5	79.4	88.8
3D CAR, FC_3	**99.3**	**93.6**	**76.7**	**89.8**

Correct classification with traning image fixed to top illumination, viewpoint angle 0°.

Results – Random Training Images

method	0°	30°	60°	avg.
Gabor features.	71.7	64.6	60.1	65.5
Opponent Gabor	**82.5**	77.7	71.7	77.3
Opponent Gabor, nm.	80.5	77.6	74.2	**77.4**
$LBP_{8,1+8,3}$, grey	61.2	61.1	65.4	62.6
$LBP^{u}_{16,2}$, grey	55.7	56.3	60.7	57.6
$LBP_{8,1+8,3}$	65.7	64.2	67.0	**65.6**
$LBP^{riu}_{16,2}$	**68.4**	60.7	57.4	62.2
2D CAR-KL, L_1	**92.4**	**91.1**	**87.5**	**90.3**
3D CAR, L_1	87.4	84.3	78.9	83.5
GMRF-KL, L_1	89.6	86.3	81.0	85.6
2D CAR-KL, FC_3	**92.3**	89.6	85.7	89.2
3D CAR, FC_3	**89.8**	86.1	80.2	85.4

Correct classification [%], using one random training image per texture.

Size of Feature Vectors

method	size	method	size
Gabor features	144	2D CAR-KL	**260**
Opponent Gabor	**252**	GMRF-KL	248
Steerable pyramid	2904	3D CAR	236
$LBP_{8,1+8,3}$, grey	512	$LBP_{8,1+8,3}$	**1536**
$LBP^{u2}_{16,2}$, grey	243	$LBP^{riu2}_{16,2}$	**54**

Size of feature vectors.

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:

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

CAR Model - Parameter Estimation II

The following notation is used:

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

and V_0 is a positive definite matrix.

CAR Model - Parameter Estimation III

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

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

The solution uses the following notations:

$$\lambda_{t-1} \;=\; V_{yy(t-1)} - V_{zy(t-1)}^T V_{zz(t-1)}^{-1} V_{zy(t-1)} \quad . \qquad (3)$$

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