***Abstract*—As a newly developed 2-D extension of the wavelet transform using multiscale and directional filter banks, the contourlet transform can effectively capture the intrinsic geometric structures and smooth contours of a texture image that are the dominant features for texture classification. In this paper, we propose a novel Bayesian texture classifier based on the adaptive model-selection learning of Poisson mixtures on the contourlet features of texture images. The adaptive model-selection learning of Poisson mixtures is carried out by the recently established adaptive gradient Bayesian Ying-Yang harmony learning algorithm for Poisson mixtures. It is demonstrated by the experiments that our proposed Bayesian classifier significantly improves the texture classification accuracy in comparison with several current state-of-the-art texture classification approaches.**

***Index Terms*—Bayesian Ying-Yang (BYY) harmony learning system, contourlet transform, model selection, Poisson mixtures, texture classification.**

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$U_i(x_t) = \alpha_j q(x_t|\theta_j)$, $j = 1, 2, \ldots, k$, $q(x_t|\theta_j) = (\theta_j^{x_t}/x_t!)e^{-\theta_j}$.

α_j : $\alpha_j = e^{\beta_j}/\sum_{i=1}^{k} e^{\beta_i}$, $j = 1, 2, \ldots, k$, $-\infty < \beta_1, \ldots, \beta_k < +\infty$. α_j β_j $\alpha_j \geq 0$ $\sum_{j=1}^{k} \alpha_j = 1$.

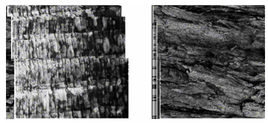
$J_t(\Theta_k)$ x_t β_j θ_j

$$\frac{\partial J_t(\Theta_k)}{\partial \beta_j} = \frac{1}{q(x_t|\Theta_k)} \sum_{i=1}^{k} A(x_t, i)(\delta_{i,j} - \alpha_j) U_i(x_t) \quad ( )$$

$$\frac{\partial J_t(\Theta_k)}{\partial \theta_j} = \frac{1}{q(x_t|\Theta_k)} A(x_t, i) \alpha_j \frac{\partial q(x_t|\theta_j)}{\partial \theta_j} \quad ( )$$

$A(x_t) = [1 - \sum_{l=1}^{k}(p(l|x_t) - \delta_{il}) \ln U_l(x_t)]$, $p(l|x_t) = (\alpha_l q(x_t|\theta_l)/q(x_t|\Theta_k))$, $\delta_{i,j}$ $(\partial q(x_t|\theta_j)/\partial \theta_j) = (\theta_j^{x_t-1}/x_t!)e^{-\theta_j}(x_t - \theta_j)$.

( ) ( ), YY β_j



(a) (b)

( ) .0000. ( ) .000 .

where $E_{i,j}^1 = i \cdot f_{i,j}^1 = (1/M_{i,j}N_{i,j}) \sum_{x=1}^{M_{i,j}} \sum_{y=1}^{N_{i,j}} |w_{i,j}(x,y)|$ and $w_{i,j}(x,y) \in c_{i,j}[\mathbf{n}]$, where $x = 1, 2, \ldots, M_{i,j}$ and $y = 1, 2, \ldots, N_{i,j}$.

$M_I \times N_I$ $a_I[\mathbf{n}]$ $a_I[\mathbf{n}]$

$$g_I^1 = \frac{1}{2^I \cdot M_I N_I} \sum_{x=1}^{M_I} \sum_{y=1}^{N_I} |w_I(x,y)|$$

$$g_I^2 = \frac{1}{2^I \cdot M_I N_I} \sum_{x=1}^{M_I} \sum_{y=1}^{N_I} \big| |w_I(x,y)| - E_I^1 \big|$$

$$g_I^3 = \frac{1}{2^I} \left[\max_{x,y} w_I(x,y) - \min_{x,y} w_I(x,y) \right]$$

where $E_I^1 = 2^I \cdot g_I^1 = (1/M_I N_I) \sum_{x=1}^{M_I} \sum_{y=1}^{N_I} |w_I(x,y)|$ and $w_I(x,y) \in a_I[\mathbf{n}]$, where $x = 1, 2, \ldots, M_I$ and $y = 1, 2, \ldots, N_I$.

$24 * I$

$$\mathbf{F} = \left(g_I^1, g_I^2, g_I^3, \mathbf{f}_I, \cdots, \mathbf{f}_1 \right)$$

where $\mathbf{f}_i = (f_{i,1}^1, \ldots, f_{i,8}^1, f_{i,1}^2, \ldots, f_{i,8}^2, f_{i,1}^3, \ldots, f_{i,8}^3)$

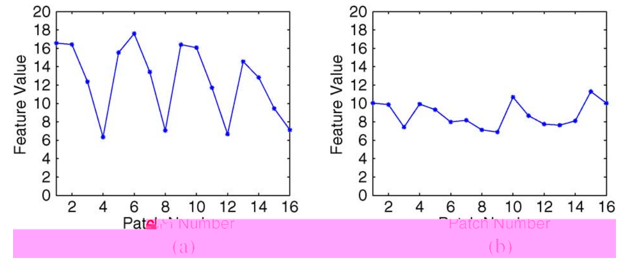
$$\mathbf{F} = (f(m))_{m=1}^{M}$$

where $M = 24 * I + 3$. $f(m)$

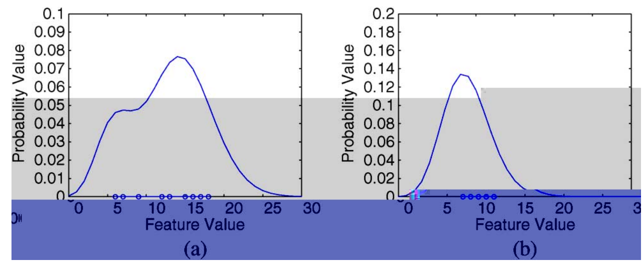
× .0000– .000 – ×

$I = 4$, ( ) ( ) $f_{3,1}^2$

( ) ( ) ( ), $f_{3,1}^2$ .0000–



$f_{3,1}^2$ ( ) .0000– ( ) .000 .–



$f_{3,1}^2$ ( ) .0000– ( ) .000 .–

$f_{3,1}^2$ .000 –

$f_{3,1}^2$

0,

(= 1)

$f_{3,1}^2$

( ) ( ) ( ) (0 . (

[illegible] $q(f(m)|\theta_{m,j})$ [illegible] $\alpha_{m,j}$ [illegible] j [illegible] k_m [illegible] $f(m)$.

[illegible] $\mathbf{F}$ [illegible] $\mathbf{F}$. [illegible]

B. Bayesian Texture Classifier Based on Poisson Mixtures

[illegible]

$$P(T_c|\mathbf{F}) = \frac{P(\mathbf{F}|T_c)P(T_c)}{\sum_{i=1}^{C} P(\mathbf{F}|T_i)P(T_i)} \quad (\ )$$

[illegible] T_c [illegible] $c\ (c = 1, 2, \ldots, C)$, $P(T_c)$ [illegible] T_c, [illegible] $P(\mathbf{F}|T_c)$ [illegible] $\mathbf{F}$ [illegible] T_c. [illegible] c^* [illegible] $P(T_c|\mathbf{F})$. $\mathbf{F}$ [illegible]

[illegible] $P(T_c)$ [illegible] $P(T_c) = (1/C)$. [illegible] $P(\mathbf{F}|T_c)$. [illegible] $P(\mathbf{F}|T_c)$ [illegible]

$$P(\mathbf{F}|T_c) = \prod_{m=1}^{M} P(f(m)|T_c) \quad (\ )$$

[illegible] $P(f(m)|T_c) = \sum_{i=1}^{k_m} \alpha_{c,m,i} q(f(m)|\theta_{c,m,i})$ [illegible] $\{\alpha_{c,m,i}, \theta_{c,m,i}, i = 1, 2, \ldots, k_m\}$ [illegible] m [illegible] $f(m)$ [illegible] T_c. [illegible] k_m [illegible]

[illegible]

[Input:] Training texture patches selected from each texture image or class (the number of training patches for each texture image is equal).
[Output:] The parameter sets of all the Poisson mixtures for each texture class.

(1) Decompose a patch of a given texture image or class c with contourlets into an output of I scales with 8 directional subbands at each scale.
(2) Calculate the value of the feature vector (15) with Eqs (8)-(13) for the patch and obtain the value of the quantized feature vector $\mathbf{F}$ by the deadzone quantization.
(3) Repeat the above two steps for all the training patches of the c-th texture class and obtain the training samples of the feature vector $\mathbf{F}$ for the c-th class.
(4) Implement the adaptive gradient BYY algorithm on the m-th components of all the training samples of the feature vector $\mathbf{F}$ for the c-th texture class, and obtain the parameters of the Poisson mixture distribution of the variable $f(m)$: $\Theta_{c,m} = \{\alpha_{c,m,i}, \theta_{c,m,i}, i = 1, 2, \cdots, k_m\}$.
(5) Repeat Step (4) for all the m components of the training samples of the feature vector $\mathbf{F}$ for the c-th texture class, and obtain the c-th class parameters: $\Theta_c = \{\Theta_{c,m}, m = 1, 2, \cdots, M\}$.
(6) Repeat the above steps for all texture classes, i.e., $c = 1, 2, \cdots, C$.

[illegible] $f(m)$. [illegible] $P(\mathbf{F}|T_c)$ [illegible] $\mathbf{F}$ [illegible] C [illegible] $c = 1, 2, \ldots, C$. [illegible] $P(\mathbf{F}|T_c)$ [illegible]

[illegible]

A. Performance Evaluation

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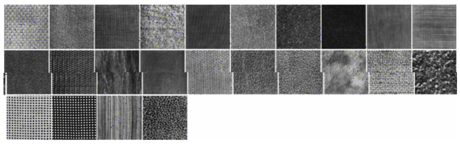

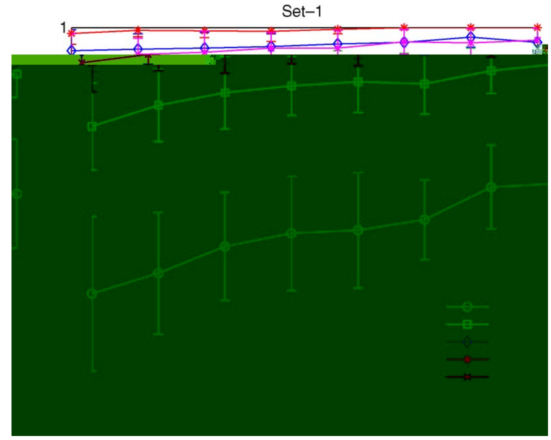
Set−1
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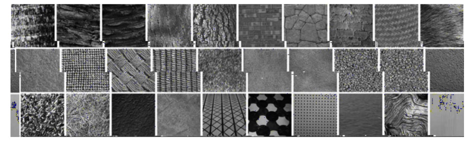
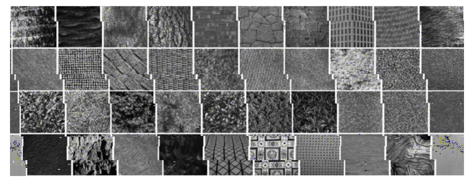
B. Comparison With the Other Existing Methods

1) Methods in the Comparison Study:

2) Data Sets:

3) Results:



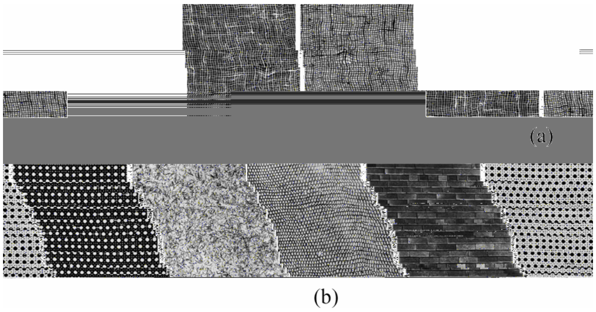


	Set-2	Set-3	Set-4	Set-5
SVD + KLD	45.60 ± 1.86	34.64 ± 2.05	64.62 ± 1.65	32.66 ± 1.10
HMT + MD	58.92 ± 2.91	56.08 ± 3.37	78.14 ± 2.93	n.a.
HMT + KNN	77.21 ± 2.02	75.73 ± 2.05	91.05 ± 1.36	n.a.
BP + L1	85.48 ± 1.98	83.91 ± 1.74	94.56 ± 0.84	78.03 ± 1.48
BC-PMC	91.60 ± 1.42	91.78 ± 1.38	97.70 ± 0.99	86.53 ± 1.12

	1	2	3	4	5		1	2	3	4	5
D1	99.38	100	93.13	58.13	48.75	D49	100	100	100	98.75	100
D3	98.75	90.63	73.75	37.50	39.38	D52	95.00	41.25	96.25	56.88	69.38
D4	100	98.75	82.50	72.50	53.75	D56	100	100	100	100	83.75
D6	100	100	100	95.63	96.88	D57	100	100	90.00	76.25	76.25
D8	100	100	98.13	62.50	56.25	D64	100	100	98.13	98.75	65.63
D9	100	96.88	84.38	83.13	30.63	D65	100	100	98.75	95.63	86.88
D10	99.38	86.25	98.75	95.00	68.13	D66	100	100	100	100	91.88
D11	100	100	100	93.13	39.38	D68	100	100	100	99.38	58.75
D15	93.75	86.88	94.38	75.63	83.75	D74	99.38	98.75	99.38	100	58.13
D17	100	100	93.13	80.63	78.75	D75	97.50	100	83.13	75.00	96.88
D18	100	100	95.00	76.25	75.00	D79	100	100	96.25	93.75	61.25
D20	100	100	98.75	89.38	75.63	D82	100	100	99.38	63.13	84.38
D21	100	100	91.88	20.00	100	D87	100	100	97.50	71.25	42.50
D22	95.00	84.38	86.88	75.63	81.88	D93	100	90.00	86.88	21.25	15.00
D25	95.63	93.13	100	99.38	45.00	D94	94.38	73.75	84.38	63.75	45.63
D26	100	99.38	100	99.38	49.38	D95	100	100	98.13	99.38	85.63
D28	100	100	96.88	80.63	45.00	D101	100	88.13	43.13	40.63	55.00
D32	100	100	93.13	89.38	55.63	D102	100	88.13	50.00	58.75	63.75
D33	100	99.38	96.88	88.75	48.13	D103	69.38	86.25	70.63	68.13	52.50
D34	100	100	100	94.38	93.75	D104	60.00	81.88	56.88	46.25	61.25
D35	100	100	75.00	36.88	43.13	D106	100	100	99.38	99.38	90.00
D37	100	89.38	98.75	74.38	53.75	D109	93.75	75.63	95.63	91.88	44.38
D46	98.13	100	98.75	88.75	61.88	D110	100	90.00	84.38	93.13	56.88
D47	100	100	94.38	74.38	75.00	D111	100	100	98.13	98.13	57.50
						Mean	97.70	94.56	91.05	78.14	64.62

C. Computational Cost

X YY Y



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