BRINT: A Binary Rotation Invariant And Noise Tolerant Texture Descriptor

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1 Abstract

Goal: Developing a theoretically simple, yet computationally efficient, noise robust, multiresolution descriptor BRINT to gray scale and rotation invariant Texture Classification (TC) based on Local Binary Pattern (LBP).

- Compact, binary descriptor
- No need for texton dictionary learning
- No tuning of parameters to deal with different datasets
- Highly robust to noise
- Invariance to illumination and rotation variations
- Good classification performance

Main components of the proposed approach

- Local Features: Novel binary features BRINT_C, BRINT_S and BRINT_M based on novel average-before-binarization idea and LBP
  → fast to build, complementary information, robust to noise, invariant to illumination and rotation changes
- Global description: Concatenation of multiple bag-of-words histogram feature from the proposed local features and multiresolution analysis
  → compact feature, efficient, training free
- Classifier: Nearest Neighbor Classifier (NNC) → simple

2 Introduction

Advantages of traditional LBP:

- ease of implementation
- no need for pre-training
- invariance to monotonic illumination changes
- low computational complexity

Disadvantages of the traditional $\text{LBP}_{r,p}$ (Refer to Table 1):

1. Rapid increase of feature dimensionality with the increase of scale
2. Failing to capture large-scale texture information
3. Sensitive to image rotation
4. Highly sensitive to noise

Weakness of $\text{LBP}^{ri}_{r,p}$:

- Having shortcomings 1,2,4 listed above
- Performing poorly for rotation invariant TC

Table 1 Number of patterns of different descriptors

Scale	(r,p)	$\text{LBP}_{r,p}$	$\text{LBP}^{ri}_{r,p}$	$\text{LBP}^{riu2}_{r,p}$	CLBP_CSM
Scale 1	$(1,8)$	256	36	10	200
Scale 2	$(2,16)$	65536	4116	18	648
Scale 3	$(3,24)$	16777216	699252	26	1352
Scale 4	$(4,32)$	2^{32}	huge	34	2312
Scale 5	$(5,40)$	2^{40}	huge	42	3528
Scale 1-5		infeasible	infeasible	106	8040

Weakness of $\text{LBP}^{riu2}_{r,p}$:

- Sensitive to noise
- Unreliability due to using uniform patterns only

Motivations

- Inheriting all advantages of $\text{LBP}^{riu2}_{r,p}$
- Avoiding the disadvantages of $\text{LBP}^{riu2}_{r,p}$
- Conquering the problem of sensitiveness to noise
- Increasing the feature distinctiveness

3 The Proposed Approach

The construction of the proposed BRINT_S descriptor is illustrated in Fig. 1. We transform the neighbor vector $\underline{\boldsymbol{x}}_{r,8q}$ by local averaging along an arc,

$$y_{r,q,i} = \frac{1}{q}\sum_{k=0}^{q-1} x_{r,8q,(qi+k)}, \quad i = 0,\ldots,7, \tag{1}$$

as illustrated in Fig. 1, such that the number of neighbors in $\underline{\boldsymbol{y}}_{r,q}$ is always eight.
Given $\underline{\boldsymbol{y}}_{r,q} = [y_{r,q,0},\cdots,y_{r,q,7}]^T$, we can trivially compute a binary pattern with respect to the center pixel:

$$\text{BNT\_S}_{r,q} = \sum_{n=0}^{7} s(y_{r,q,n} - x_c)2^n \tag{2}$$

$\text{BRINT\_S}_{r,q}$ is defined as

$$\text{BRINT\_S}_{r,q} = \min\{ROR(\text{BNT\_S}_{r,q}, i) | i = 0,\cdots,7\}, \tag{3}$$

We compute a binary pattern BNT_M (Binary Noise Tolerant Magnitude) based on via

$$\text{BNT\_M}_{r,q} = \sum_{n=0}^{7} s(z_{r,q,n} - \mu^l_{r,q})2^n, \tag{4}$$

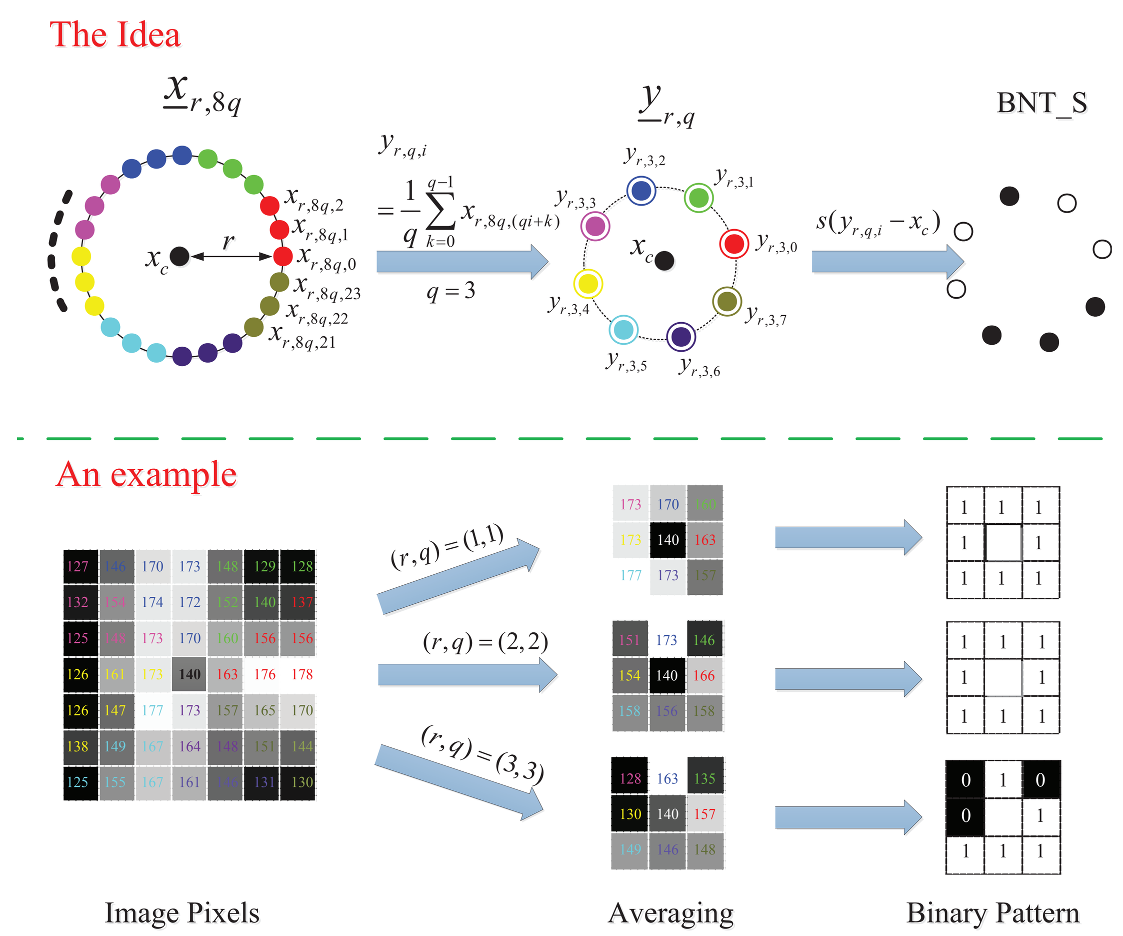

Fig. 1 Illustration of the proposed BNT_S descriptor

where μ_l is the local thresholding value:

$$\mu^l_{r,q} = \frac{1}{8}\sum_{n=0}^{7} z_{r,q,n}. \tag{5}$$

With BNT_M defined, BRINT_M is defined as

$$\text{BRINT\_M}_{r,q} = \min\{ROR(\text{BNT\_M}_{r,q}, i) | i = 0,\ldots,7\}. \tag{6}$$

Finally, we also represent the center pixel in one of two bins:

$$\text{BRINT\_C}_r = s(x_c - \mu_{I,r}) \tag{7}$$

where $\mu_{I,r}$ is the mean of the whole image excluding boundary pixels:

$$\mu_{I,r} = \frac{1}{(M-2r)(N-2r)}\sum_{i=r+1}^{M-r}\sum_{j=r+1}^{N-r} x(i,j). \tag{8}$$

Multiresolution analysis:
We evaluated up to *nine* scales (Multiple-Scale, MS). At each scale (Single-Scale, SS), we adopt the $\text{BRINT\_CS}_{r,q}\text{\_CM}_{r,q}$ descriptor, meaning the joint histogram BRINT_C $*$ $\text{BRINT\_S}_{r,q}$ concatenated with BRINT_C $*$ $\text{BRINT\_M}_{r,q}$.
Classifier: The histogram features are classified according to their normalized histogram feature vectors $\underline{\boldsymbol{h}}_i$ and $\underline{\boldsymbol{h}}_j$, using χ^2 distance metric $\chi^2(\underline{\boldsymbol{h}}_i,\underline{\boldsymbol{h}}_j) = \frac{1}{2}\sum_k \frac{[\underline{\boldsymbol{h}}_i(k)-\underline{\boldsymbol{h}}_j(k)]^2}{\underline{\boldsymbol{h}}_i(k)+\underline{\boldsymbol{h}}_j(k)}$. The NNC classifier is used.

4 Results

Table 2 BRINT vs. conventional CLBP at single scales.

	Single Scale								
Methods	SS1	SS2	SS3	SS4	SS5	SS6	SS7	SS8	SS9
MS2	MS3	MS4	MS5	MS6	MS7	MS8	MS9		
Outex_TC10									
BRINT_CS_CM	91.87	96.43	96.04	94.04	95.16	94.51	91.61	92.16	93.78
$\text{CLBP\_CS}^{ri}\text{\_CM}^{ri}$	91.87	95.34	89.14	84.95	80.89	78.10	73.83	70.44	67.92
$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$	95.68	98.23	98.72	98.96	98.05	97.58	97.71	96.77	96.30
Outex_TC12_000									
BRINT_CS_CM	86.46	93.38	94.47	91.06	92.15	89.86	89.65	89.38	90.72
$\text{CLBP\_CS}^{ri}\text{\_CM}^{ri}$	86.46	92.62	88.56	81.27	79.86	77.62	73.36	69.63	67.94
$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$	89.81	94.31	94.88	93.98	90.56	87.85	88.26	88.29	87.71
Outex_TC12_001									
BRINT_CS_CM	88.50	93.98	94.40	90.81	92.27	90.42	88.80	89.70	90.97
$\text{CLBP\_CS}^{ri}\text{\_CM}^{ri}$	88.50	93.01	87.82	81.78	79.26	76.48	73.12	69.21	68.75
$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$	91.44	94.47	93.19	92.41	88.98	85.83	86.90	88.01	86.90

Table 3 BRINT vs. conventional CLBP at multiple scales.

	Multiple Scales							
Methods	MS2	MS3	MS4	MS5	MS6	MS7	MS8	MS9
Outex_TC10								
BRINT_CS_CM	96.95	98.52	99.04	99.32	99.32	99.30	99.40	99.35
$\text{CLBP\_CS}^{ri}\text{\_CM}^{ri}$	96.28	95.21	93.44	91.56	90.60	89.14	88.07	87.58
$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$	98.41	99.30	99.43	99.45	99.51	**99.53**	99.48	99.48
Outex_TC12_000								
BRINT_CS_CM	94.24	96.23	97.04	97.18	97.22	97.43	97.64	**97.69**
$\text{CLBP\_CS}^{ri}\text{\_CM}^{ri}$	93.17	94.56	93.29	91.25	88.82	87.55	86.92	86.41
$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$	95.63	96.81	96.67	96.23	95.95	96.00	96.00	95.97
Outex_TC12_001								
BRINT_CS_CM	94.35	96.34	97.29	97.41	97.85	97.99	98.29	**98.56**
$\text{CLBP\_CS}^{ri}\text{\_CM}^{ri}$	93.26	93.63	92.04	90.88	89.47	88.43	87.29	86.78
$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$	88.01	86.90	95.12	95.63	95.35	94.58	94.40	94.19
94.21	93.91							

Table 4 BRINT vs. state-of-the-art methods.

		Outex Database		
Classifier	Method	TC10	TC12_000	TC12_001
NNC	Ours: BRINT_CS_CM (MS9)	**99.35**	97.69	**98.56**
NNC	CLBP_CSM [7]	99.14	95.18	95.55
	CLBC_CSM [8]	98.96	95.37	94.72
	$\text{LBP}^{riu2}_{P,R}/\text{VAR}_{P,R}$ [1]	97.7	87.3	86.4
	$\text{LBPV}^{u2}_{P,R}\text{GM}^{Pr2-1}_{PD2}$ [12]	97.63	95.06	93.88
	$\text{dis(S+M)}^{ri}_{N,R}$ [9]		97.0	96.5
	VZ-MR8 [15]	93.59(◇)	92.55(◇)	92.82(◇)
	VZ-Patch [16]	92.00(◇)	91.41(◇)	92.06(◇)
SVM	DLBP+NGF [3]	99.1	93.2	90.4

Table 5 BRINT performance as a function of noise.

Databases	Features	Classification Accuracies (%)					
		SNR=100	SNR=30	SNR=15	SNR=10	SNR=5	SNR=3
Outex_TC10	BRINT_CS_CM (MS9, NNC)	97.76	96.48	**95.47**	**92.97**	88.31	71.51
	$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$ (MS9, NNC)	**99.30**	**98.12**	94.58	86.07	51.22	28.65
	LBP^{riu2} (MS3, NNC) [1]	95.03	86.93	67.24	49.79	24.06	12.97
Outex_TC12_000	BRINT_CS_CM (MS9, NNC)	95.95	**93.59**	**91.32**	**90.49**	83.68	69.70
	$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$ (MS9, NNC)	**96.16**	93.54	88.73	83.52	52.22	29.35
	LBP^{riu2} (MS3, NNC) [1]	91.30	82.55	60.25	47.31	24.07	13.63
Outex_TC12_001	BRINT_CS_CM (MS9, NNC)	**96.92**	**95.14**	**93.66**	**92.29**	84.77	71.02
	$\text{CLBP\_CS}^{riu2}\text{\_CM}^{riu2}$ (MS9, NNC)	95.95	93.66	88.36	81.71	53.43	26.81
	LBP^{riu2} (NNC) [1]	90.72	79.17	60.74	45.81	25.02	12.55