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Performance Analysis of Local Binary Pattern Variants in Texture Classification

Ch. Sudha Sree[1], M. V. P Chandra Sekhara Rao[2]
[1,2]Department of CA, Department of CSE, R.V.R &J.C College of Engineering
Guntur, India

Abstract--Texture classification is a major issue in image analysis and pattern recognition. A number of methods are proposed in the literature including Local Binary Pattern (LBP). The LBP variant (s) plays an active role to extract texture features for texture classification. These are rotation invariant, noise sensitive or noise insensitive mehods. Each method has its own advantages and disadvantages. This paper is focused to provide a comparative analysis by evaluating the nine LBP variants using three well-known benchmark texture databases OUTEX, CUReT, UIUC using the nearest-neighbourhood classifier. The nine LBP variants are rotation invariant and uniform LBP (LBP^{riu2}), rotation invariant LBP (LBP^{ri}), Local Ternary Pattern (LTP), Variance (VAR), LBP and VAR (LBP/VAR), Completed Local Binary Pattern (CLBP), Completed Local Binary Count (CLBC), Adjacent Evaluation Completed Local Binary Pattern (AECLBP), Adjacent Evaluation Local Ternary Pattern (AELTP). The experimental results demonstrated that, Adjacent Evaluation Completed Local Binary Pattern (AECLBP) exhibits significant improvement in classification accuracy when compared to remaining LBP variants.

Keywords: Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Completed Local Binary Pattern (CLBP), Completed Local Binary Count (CLBC), Adjacent Evaluation Completed Local Binary Pattern (AECLBP), texture classification, rotation invariant.

1. Introduction

Texture classification has an important role in image processing and computer vision applications, such as character recognition [1], rock classification [2], wood species recognition [3], face detection [4], fabric classification [5], geographical landscape segmentation [6], image retrieval, remote sensing and medical image analysis.The texture classification methods can be categorized into statistical methods, model based methods and structural methods. The statistical methods are proposed, based on statistics selected features from spatial distribution of neighboring pixels in an image, such as polorograms with generalized co-occurrence matrices [7], texel property histogram [8], Fourier descriptors [9] and moment invariant methods [10]. Model based approaches are developed based on probability model or linear combination of set of basic functions. The model based methods, for example are circular simultaneous autoregressive model [11], steerable pyramid [12], Gaussian Markov random fields [13]. Structural methods are developed based on the well-defined primitives and spatial arrangements. The structural methods in the literature are topologically invariant texture method [14], improved iterative morphological decomposition [15]. All these methods provide the texture classification either as rotation variant, or invariant, and either noise sensitive or insensitive.

Local Binary Pattern (LBP) is a well-known method of texture classification and is a combination of structural and statistical approach. Various Local Binary Pattern methods are proposed in literature. These methods gain popularity due to their impressive classification accuracy on texture database. The Local Binary Pattern (LBP) [16] is developed by Ojala et al in 2002. The two steps in Local Binary Pattern are thresholding and encoding. In thresholding, local gray scale difference is computed with neighborhood pixels around the selected centre pixel with radius R(1, 2, 3). The threshold value may be either one or zero, based on the difference value. The encoding step converts the bit pattern of threshold into decimal number. Though the LBP is a successful method in texture classification, it is sensitive to rotation and also has vast majority patterns. To overcome the disadvantage, Ojala et al proposed a uniform Local Binary Pattern with rotation invariance ($LBP_{P,R}^{riu\,2}$) [16]. It is used in different applications such as face recognition [17], shape localization [18]. The uniform Local Binary Pattern with rotation invariance ($LBP_{P,R}^{riu\,2}$) is invariant to gray scale difference. Thus it rejects contrast of local image. So contrast of image is provided by local Variance method (VAR) [16] with rotation invariance and it is variant to gray scale difference. The joint distribution of local variance and $LBP_{P,R}^{riu\,2}$ [16] provides significant classification accuracy than individual

$LBP_{P,R}^{riu\,2}$and VAR. Guo et al developed a Completed Local Binary Pattern (CLBP) [19] for texture classification to improve the performance of classification accuracy when compared to LBP. CLBP and LBP are not totally rotation invariant. To overcome the disadvantage of CLBP and LBP,Yang Zhao et al proposed a Completed Local Binary Count (CLBC) [20]. Local Binary Pattern is not only rotation variant but also sensitive to noise. As a solution, Local Ternary Pattern (LTP) [21] is proposed by Tan and Triggs which is less sensitive to noise when compared to LBP. Another pitfall of LBP is, it does not provide the dissimilarity between patterns. Completed Local Ternary Pattern (CLTP) [22] is proposed by Taha H. Rassem and Bee EeKhoo with the extension of LTP. NishantShrivastava·VipinTyagi in 2014 developed a Completed Local Structural Pattern(CLSP) [23] with global information. But CLSP is sensitive to noise, thus NishantShrivastava.VipiniTyagi further developed Robust Local Structural Pattern (RLSP) [23] and made the method as insensitive to noise. It has achieved good classification accuracy when compared to CLBP and LBP. Adjacent Evaluation Local Binary Pattern (AELBP), Adjacent Evaluation Completed Local Binary Pattern (AECLBP) and Adjust Evaluation Local Ternary Pattern (AELTP) [24] are proposed by Kechen Song et al. These are robust to noise when compared to CLBP and LBP.In this paper we have studied the performance of these methods in classification using three benchmark databases.

The remaining section of this paper is organized as follows:Section 2 describes the different LBP variant (LBPriu2, LBPri, VAR, LBP/VAR, LTP, CLBP, CLBC, AELBP, AECLBP, AELTP) methodologies. Experimental results and discussions are presented in section 3 and conclusions are included in section 4.

2.Related Work

The description of Local Binary Pattern (LBP) is as follows.

2.1. Local Binary Pattern (LBP)

LBP is a texture descriptor that characterizes the texture image using two steps, thresholding and encoding. Given a pixel of image, LBP computes the local gray scale difference by comparing it with each of its neighbor pixel(s) in a selected radius of R. A zero is assigned when the difference is less than zero and in remaining values it is taken as 1. A decimal number is computed using these thresholds in the encoding step. The LBP operator [16] for a given pixel of the image is as follows:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p, s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (1)$$

Where g_c and $g_p\,(p = 0, \ldots\ldots P-1)$are the gray values of centre pixel and its neighbors. P is the maximum number of neighbors in the selected neighborhood of radius R. A histogram is to be calculated to represent the texture of the image after computing the LBP coding for each pixel of the image. The two steps of LBP operator is shown in Figure 1.

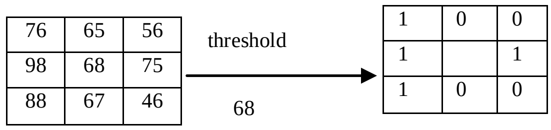

Figure1: illustration of LBP operator

The rotation invariant LBP [16] is defined as follows:

$$LBP_{P,R}^{ri} = \min\{(ROR(LBP_{P,R}, i) \mid i = 0,1, \ldots P-1)\} \, (2)$$

Where$ROR(x, i)$ performs a circular bit-wise right shift on the P-bit number x, i times.Ojala et al have developed uniform patterns to minimize the vast majority pattern in local binary pattern. The uniform values for LBP [16] are defined as the number of bitwise transitions in the pattern as follows:

$$U(LBP_{P,R}) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \quad (3)$$

Where g_c, g_p, andP are defined as in Eq. (1). The uniform pattern (U ($LBP_{P,R}$)) is a pattern with transitions not more than 2. Rotation invariance has a significant role in texture classification.The rotation invariant LBP is combined with uniform patterns [16]. Rotation invariant and uniform local binary pattern is described as follows:

$$LBP_{P,R}^{riu\,2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c), & \text{if } U(LBP_{P,R} \leq 2) \\ P+1, & \text{otherwise} \end{cases} \quad (4)$$

Where g_c, g_p, P are defined as in Eq.(1). $LBP_{P,R}^{riu\,2}$is invariant to gray scale values, thus it discards the contrast. The contrast of image is required without gray-scale invariant, the local variance (VAR) [16] of image is proposed. It is defined as follows:

$$VAR_{P,R} = \frac{1}{P}\sum_{p=0}^{P-1} (g_p - \mu)^2,$$

$$\text{where } \mu = \frac{1}{P}\sum_{p=0}^{P-1} g_p \quad (5)$$

Here g_c, g_p , P are defined as in Eq.(1). $LBP_{P,R}^{riu\,2}$ and VAR complement with each other, based on contrast. The joint distribution of $LBP_{P,R}^{riu\,2}$ and VAR ($LBP_{P,R}^{riu\,2}$ /VAR) became a powerful rotation invariant measure.

2.2. Local Ternary Pattern (LTP)

Usage of central pixel as a threshold in Local Binary Pattern made LBP is sensitive to noise, mainly in the near uniform image regions. A small change of the central pixel (60 to 65) greatly changes the LBP code and is shown in Figure 2. To overcome the disadvantage, Local Ternary Pattern (LTP) [21] has been developed.

The LTP operator is defined as follows:

$$\mathrm{LTP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)\,2^p,\ \ s(x) = \begin{cases} 1, & x \geq t \\ 0, & -t < x < t \\ -1, & x \leq -t \end{cases} \quad (6)$$

Where g_c, g_p, P are defined as in Eq.(1) and t is a threshold, defined by user. Conventional 2-valued (0,1) LBP code is extended to 3-valued (-1, 0, 1) ternary code by using threshold t. The ternary code made the LTP insensitive to noise but it is no longer invariant to monotonic gray scale transformation.

45	65	70
61	60	34
64	63	67

60 to 65 → Noise

45	65	70
61	65	34
64	63	67

LBP: 01101111 LBP : 01101000

Figure2: Example for LBP is noise sensitive

2.3. Completed Local Binary Pattern (CLBP)

The CLBP [19] improves the capability of LBP by decomposing the image local differences into two complementary components signs (s_p) and magnitudes (m_p) and are defined as follows:

$$s_p = s(g_p - g_c),\ m_p = |g_p - g_c| \quad (7)$$

Where g_c, g_p are defined as in Eq.(1). CLBP is defined with a set of three operators, CLBP_S, CLBP_M and CLBP_C. Among the three operators CLBP_S is as same as LBP. CLBP_M provides the local variance of magnitude. It is defined as follows:

$$\mathrm{CLBP\_M}_{P,R} = \sum_{p=0}^{P-1} t(m_p, c)\,2^p,$$

$$t(x,c) = \begin{cases} 1, & x \geq c \\ 0, & x < c \end{cases} \quad (8)$$

where cis the mean value of m_p of the whole image and g_c, g_p, P are as described in Eq.(1).

CLBP_C operator provides the local central information. It is defined as follows:

$$\mathrm{CLBP\_C}_{P,R} = s(g_c - c_l) \quad (9)$$

Here c_l is the average gray level of whole image. A significant improvement for rotation invariant texture classification accuracy is obtained by combining the three operators [19].

2.4. Adjacent Evaluation Local Binary Pattern (AELBP)

As conventional LBP is sensitive to noise, AELBP [24] has been developed which is robust to noise. AELBP generates an evaluation window to each neighbor around the neighborhood centre g_c and a value of a_p is calculated at each neighbor. AELBP computes the local binary code by comparing g_c and a_p. It is defined as follows:

$$\mathrm{AELBP}_{P,R} = \sum_{p=0}^{P-1} s(a_p - g_c)2^p,$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (13)$$

Where g_c is defined as in Eq. (1), P is number of neighborhood pixels and a_p is mean value of p^{th} evaluation window excluding the value of evaluation center and R is radius. The process of AELBP is as follows

1. Calculation of a_p:An evaluation window of size WXW (W is odd numbers) is set to each neighbor g_p of the neighborhood center g_c. The value of a_p is computed at each neighbor g_p, of the neighborhood center g_c with mean value of gray values in the p^{th} evaluation window excluding the value of center g_p. If window size W is one, then AELBP is identical to LBP.
2. Coding the Local Binary Pattern: LBP can characterize the encoding step based on the difference of a_p and g_c values after completing the thresholding step.

The difference between LBP and AELBP is in the computation of thresholding step. That is in LBP the central pixel g_c is compared with its neighborhood pixel g_p with radius R where as in AELBP, the central pixel g_c is compared with its neighbor a_p with radius R.

2.4.1. Adjacent Evaluation Completed Local Binary Pattern (AECLBP)

Similar to CLBP, AELBP is enhanced to AECLBP. AECLBP is divided into two components, sign component (s_p), and magnitude component (m_p). They are described as follows:

$$s_p = s(a_p - g_c),\ \ m_p = |a_p - g_c| \quad (14)$$

AECLBP has AECLBP_S, AECLBP_M and AECLBP_C operators. AECLBP_S is equivalent to conventional AELBP. AECLBP_M gives the local variance of magnitude. It is defined as follows:

$$\mathrm{AECLBP\_M}_{P,R} = \sum_{p=0}^{P-1} t(m_p - c)2^p,$$

$$t(x,c) = \begin{cases} 1, & x \geq c \\ 0, & x < c \end{cases} \quad (15)$$

Where c denotes the mean value of m_p in the whole image and g_c, P are described as in Eq.(1), a_p defined in Eq. (13). AECLBP_C operator extracts the local central information. It is defined as follows:

$$\mathrm{AECLBP\_C}_{P,R} = s(g_c - c_l) \quad (16)$$

Where c_l is the average gray level of whole image. A significant improvement for rotation invariant texture classification is obtained by combining these three operators (AECLBP_S, AECLBP_M, and AECLBP_C) [19].

2.4.2. Adjacent Evaluation Local Ternary Pattern (AELTP)

Adjacent Evaluation Local Ternary Pattern (AELTP) is proposed by extending binary values (0,1) of AELBP into ternary values (-1,0,1). It is defined as follows:

$$\mathrm{AELTP}_{P,R} = \sum_{p=0}^{P-1} s(a_p - g_c)\,2^p, \quad s(x) = \begin{cases} 1, & x \geq t \\ 0, & -t < x < t \\ -1, & x \leq -t \end{cases} \quad (17)$$

Where t is a threshold and a_p, g_p, g_c, P, R defined asin Eq. (13) and Eq. (1). The difference between LTP and AELTP is, the central pixel which is compared with $a_p$in AELTP. But in LTP central pixel is compared with g_p.

2.5. Completed Local Binary Count (CLBC)

Experimentally it is found that the number of specified rotation invariant structural patterns is too few to contain abundant structural information. It is also observed that some rotation invariant patterns of LBP may change after rotation and interpolation [20]. So the LBP variants, whose have similar encoding proceed of LBP, suffered with rotation invariance. As a solution, Local Binary Count (LBC) is developed and further it is enhanced to CLBC [20] for improved performance in classification of textures.

LBC is defined asfollows:

$$\mathrm{LBC}_{P,R} = \sum_{p=.}^{P-1} s(g_p - g_c), \quad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (10)$$

Where g_c, g_p, P are defined as in Eq.(1). LBC totally avoids the microstructure information. LBC has been extended to Completed LBC (CLBC) with three operators CLBC_S, CLBC_M and CLBC_C. The three operators can be combined either jointly or hybridly like CLBP. CLBC_S is same as LBC.

CLBC_M and CLBC_C are defined as follows:

$$\mathrm{CLBC\_M}_{P,R} = \sum_{p=0}^{P-1} t(m_p, c), \quad t(x,c) = \begin{cases} 1, & x \geq c \\ 0, & x < c \end{cases} \quad (11)$$

where c denotes the mean value of m_p in the whole image and

$$m_p = |g_p - g_c| \, CLBC_{C_{P,R}} = s(g_c - c_l) \quad 12)$$

Where g_c, g_p, P are described as in Eq.(1). c_l is the average gray level of whole image.

3. Experimental results and Discussions

Experiments are conducted to study the performance of existing LBP variant texture descriptor methods using three bench mark huge databases. They are Outex database [25], CUReT database [26], and UIUC database [27].

Dissimilarity measuring framework

Various metrics are proposed for measuring the dissimilarity between two histograms such as a histogram intersection, log-likelihood ratio, and chi-square statistics. Thus chi-square statistics [19][20] is used. The distance between two histograms H=h_i and K=k_i where (i=1,2,3,---B) can be defined mathematically as follows:

$$\mathrm{Dissimilarity}_{\chi^2}(H,K) = \sum_{i=1}^{B} \frac{(h_i - k_i)^2}{h_i + k_i} \quad (18)$$

In this work, the nearest neighborhood classifier is used for classification. The complete details of the three databases furnished as follows.

Outex Database

Outex_TC_0010 (TC10) and Outex_TC_0012 (TC12) are used for the experimentation. The TC10 and TC12 contain 24 classes of texture images. These were collected under three illuminations ("horizon", "inca" and "t184") and nine various rotation angles (0^0, 5^0, 10^0, 15^0, 30^0, 45^0, 60^0, 75^0, and 90^0). Each class has 20 non-overlapping 128x128 texture images under each situation.

For TC10, 480 images from this database are used as training data. These are the images of each class under "inca" illumination with "0^0" rotation of angle. The remaining images from the same database 3840 are used as testing data. The testing data is images of each class under same illumination with remaining rotation of angles (5^0, 10^0, 15^0, 30^0, 45^0, 60^0, 75^0, and 90^0). For TC12, The data of TC10 is taken as trained data. Images under "t184"or "horizon" illumination of TC12 are used for testing. The experimental results of TC10, TC12 (t184), TC12(horizon) are shown in Table 1.

Table 1: Classification rates(%) on TC10 and TC12 database

	R=1 P=8				R=2 P=16				R=3 P=24			
	TC10	TC12		Average	TC10	TC12		Average	TC10	TC12		Average
		t184	Horizon			t184	Horizon			t184	Horizon	
LTP	94.14	75.88	73.96	81.33	96.95	90.16	86.94	91.35	98.2	93.59	89.42	93.74
LBP^{riu2}	84.81	65.46	63.68	71.32	89.40	82.27	75.21	82.29	95.08	85.05	80.79	86.97
LBP^{ri}	78.8	71.97	69.98	73.58	91.72	88.26	88.47	89.48	-	-	-	-
VAR	88.39	61.48	62.34	70.74	86.61	63.26	68.94	72.94	-	-	-	-
LBP^{riu2}/VAR	95.63	75.93	74.91	82.16	97.08	84.40	83.19	88.22	-	-	-	-
CLBP_S	84.81	65.46	63.68	71.32	89.40	82.27	75.21	82.29	95.08	85.05	80.79	86.97
CLBC_S	82.94	65.02	63.17	70.38	88.67	82.57	77.41	82.88	91.35	83.82	82.75	85.97
AECLBP_S	82.34	73.68	68.71	74.91	90.29	83.54	78.52	84.12	89.92	83.29	81.06	84.76
CLBP_M	81.74	59.30	62.77	67.94	93.67	73.79	72.40	79.95	95.52	81.18	78.65	85.12
CLBC_M	78.96	53.63	58.01	63.53	92.45	70.35	72.64	78.48	91.85	72.59	74.58	79.67
AECLBP_M	83.62	66.55	63.50	71.22	86.67	73.13	75.14	78.31	92.86	73.96	78.91	81.91
CLBP_S_M	94.66	82.75	83.14	86.85	97.89	90.55	91.11	93.18	99.32	93.58	93.35	95.42
CLBC_S_M	95.23	82.12	83.59	86.98	98.10	89.95	90.42	92.82	98.70	91.41	90.25	93.45
AECLBP_S_M	95.49	87.38	88.13	90.33	97.89	91.88	91.83	93.87	99.01	93.80	93.91	95.57
CLBP_S_M_C	96.56	90.30	92.29	93.05	98.72	93.54	93.91	95.39	98.93	95.32	94.53	96.26
CLBC_S_M_C	97.16	89.79	92.92	93.29	98.54	93.26	94.07	95.29	98.78	94.00	93.24	95.34
AECLBP_S_M_C	97.58	91.83	91.81	93.74	98.80	95.42	94.70	96.31	99.19	96.83	95.05	97.02
AELTP	92.73	79.14	76.34	82.74	96.69	89.24	86.41	90.78	97.55	91.30	88.45	92.43

Table2: Classification rates(%) on CUReT database

	R=1 P=8				R=2 P=16				R=3 P=24			
	6	12	23	46	6	12	23	46	6	12	23	46
LTP	65.17	74.61	80.85	87.74	68.72	80.18	86.17	91.16	72.76	82.42	87.19	91.52
LBP^{riu2}	60.36	69.05	74.64	81.32	63.38	72.70	79.28	84.53	67.86	75.51	81.65	86.35
LBP^{ri}	66.60	75.10	80.47	86.06	68.34	75.27	80.61	85.21	-	-	-	-
VAR	43.27	49.63	55.55	61.72	41.16	45.31	50.61	55.95	-	-	-	-
LBP^{riu2}/VAR	71.56	80.90	86.96	92.91	73.20	81.60	88.19	94.23	-	-	-	-
CLBP_S	60.36	69.05	74.64	81.32	63.38	72.70	79.28	84.53	67.86	75.51	81.65	86.35
CLBC_S	58.81	66.76	72.61	77.76	60.24	67.79	73.63	79.00	61.95	68.05	73.79	77.69
AECLBP_S	58.43	65.78	71.82	77.94	62.83	72.30	78.31	83.14	65.19	73.69	80.26	85.42
CLBP_M	54.19	60.77	67.21	75.73	59.60	68.25	76.52	81.32	64.86	71.43	80.42	87.31
CLBC_M	45.06	50.98	56.33	64.33	50.27	59.49	65.91	71.53	52.23	59.26	69.11	75.20
AECLBP_M	56.58	65.49	72.46	77.48	60.79	69.84	79.62	84.43	65.23	74.02	81.16	86.64
CLBP_S_M	74.41	82.9	88.9	92.62	76.47	84.32	89.92	93.30	77.90	84.73	90.99	93.97
CLBC_S_M	72.17	80.82	87.00	91.59	73.79	81.78	89.36	93.30	72.84	80.76	88.29	93.01
AECLBP_S_M	73.69	82.40	89.67	93.23	76.25	83.77	90.45	94.01	77.22	85.76	91.04	95.12
CLBP_S_M_C	76.82	84.96	91.54	95.33	78.07	86.45	92.30	95.40	78.99	86.37	92.51	95.90
CLBC_S_M_C	75.09	83.32	90.66	94.23	76.65	84.12	92.42	95.15	76.00	83.38	91.35	95.01
AECLBP_S_M_C	77.07	84.84	91.90	94.94	78.50	86.11	92.61	95.72	79.03	87.03	92.61	96.54
AELTP	67.12	76.76	84.20	89.27	71.27	80.51	86.89	90.77	72.04	81.19	87.57	91.87

Table3: Classification rates(%) on UIUC database

	R=1 P=8				R=2 P=16				R=3 P=24			
	5	10	15	20	5	10	15	20	5	10	15	20
LTP	50.06	58.27	64.64	67.8	61.26	71.33	74.40	78.20	60.91	74.53	78.72	83.40
LBP^{riu2}	41.02	49.20	52.16	56.40	41.25	52.00	58.08	57.20	45.25	56.26	59.84	64.60
LBP^{ri}	43.89	50.80	57.12	63.20	49.26	60.67	66.56	71.80	-	-	-	-
VAR	36.34	43.73	47.84	49.80	39.20	47.33	50.40	51.00	-	-	-	-
LBP^{riu2}/VAR	51.77	63.07	67.84	67.80	58.86	67.33	71.04	73.80	-	-	-	-
CLBP_S	41.02	49.20	52.16	56.40	41.25	52.00	58.08	57.20	45.25	56.26	59.84	64.60
CLBC_S	40.00	48.80	51.36	56.80	42.17	54.27	58.56	62.00	48.34	59.87	62.72	67.80
AECLBP_S	37.71	48.13	54.40	57.40	42.51	51.06	59.04	60.6	46.63	57.07	61.44	62.4
CLBP_M	40.45	52.26	55.84	57.40	58.17	66.00	69.92	72.40	58.40	67.33	71.52	76.40
CLBC_M	40.57	46.26	49.60	53.40	51.09	60.00	65.92	69.80	54.17	61.07	67.84	70.00
AECLBP_M	45.94	57.47	58.08	61.80	56.00	66.8	67.36	72	60.57	68.4	71.36	75.4
CLBP_S_M	66.05	75.86	80.48	83.80	73.14	82.00	85.76	88.60	75.08	84.26	86.40	90.00
CLBC_S_M	66.17	75.47	80.00	82.80	76.11	82.67	86.24	89.80	76.46	86.67	87.36	89.80
AECLBP_S_M	67.77	76.80	82.08	86	72.57	82.26	86.40	88.8	78.17	85.73	88.32	92.2
CLBP_S_M_C	75.20	84.93	86.08	88.20	81.26	86.40	89.12	92.20	79.65	87.06	87.52	93.00
CLBC_S_M_C	75.43	85.47	86.88	88.60	80.69	87.20	88.16	92.60	81.02	86.80	89.28	92.40
AECLBP_S_M_C	78.17	84.40	85.28	89.80	80.46	88.53	87.84	92	82.97	89.07	91.2	94.2
AELTP	50.86	61.6	62.88	69.2	64.91	71.33	73.28	79.60	63.89	75.73	77.60	82.80

CUReT Database

The CUReT database contains 61 classes of textures retrieved at various viewpoints and illumination orientations. Each class has 92 images. As in [19][20] N images for each class are randomly selected as train data and remaining (92-N) images for each class are selected as test data. Experimental results of classification accuracy for N=6, 12, 23 and 46 is demonstrated in Table 2.

UIUC Database

UIUC database contains 25 classes. Each class has 40 images with resolution of 640x480. These images are captured under significant viewpoint variations. N images for each class are randomly selected as train data and remaining (40-N) images for each class are selected as test data for classification [19][20]. Experimental results for N=5, 10, 15, and 20 is presented in Table3.

LBP Variant methods are validated using classification performance. It is defined by using formula.

$$\text{Classification Performance}=\frac{N_{right}}{M}\times 100 \qquad (19)$$

Where N_{right} is the number of right classifications and M is number of images in test data.

Discussions:

The findings of the study on classification performance of LBP variants are provided as follows: We have tested on three bench mark databases Outex, CUReT, UIUC. From Table 1, AECLBP_ S_M_C has achieved classification accuracy 93.74%, 96.31%, and 97.02% in avarage with radius R=1, 2 and 3 using Outex. Table 2 demonstrates the superiority of AECLBP_S_M_C in various experiments with classification accuracies 94.94%,95.72%, and 96.54% at radius R=1, 2, and 3 when N=46 on CUReT. From Table 3, AECLBP_S_M_C has achieved classification accuracy 89.80%, 92.00%, and 94.20% by conducting experiment on UIUC with radius R=1, 2, and 3 when N=20. AECLBP_S_M_C has achieved better classification accuracy when compared to local binary pattern variants (LBP^{riu2}, LBP^{ri}, VAR, LBP^{riu2}/VAR, CLBP_S_M_C, CLBC_S_M_C, AELTP, LTP).

4. Conclusion

As LBP has a number of variants, this paper studied the performance of various LBP variants (LBP^{riu2}, LBP^{ri}, VAR, LBP^{riu2}/VAR, CLBP, CLBC, AECLBP, LTP, AELTP) applying on three huge databases. Among these LBP^{riu2}, LBP^{ri},

LBP^{riu2}/VAR, CLBP, and CLBC are noise sensitive and AECLBP, LTP, AELTP are robust to noise. In average AECLBP performs well when compared to all other noise insensitive texture methods. CLBP,CLBC performs well in classification among the noise sensitive texture methods. From literature, except CLBC, the encoding process of remaining LBP variants similar to LBP. So, the invarint patterns of remaining LBP variants may vary after rotation. There is a need to develop noise insensitive and rotation inavariant methods for many texture classification applications. Developing new noise insensitive and rotation invariant texture classification methods is our future endeavor.

5. References

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