Survey on Extraction of Texture based Features using Local Binary Pattern

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***Abstract*—Local Binary Pattern (LBP) is one of the operator, which is used to extract the texture features. It is used in different applications such as texture classification, face recognition, face expression recognition, gender classification and etc. In this paper we have studied existing improvements of Local Binary Pattern.**

Keywords*—*Texture;Local Binary Patterns;Texure analysis

I. INTRODUCTION

The basic work of digital image processing and computer vision is proper representation of image features. In the application analysis of images, texture, color, spatial relationship and shape features plays important role. Therefore, in image processing, how to retrieve texture feature information accurately and effectively is a dynamic topic for researcher.

In texture analysis and face recognition applications, local binary pattern (LBP)[1-4] feature retrieval method has made a remarkable progress. So it has many improvement methods. LBP method is not relatively simple and with low computation complexity and also has some properties. Those properties are gray scale invariance, rotational invariance, and other significant advantages. So LBP is used in Biological and medical image analysis, image matching, pedestrian and car target detection and tracing. Even though great success of LBP in early applications, its practical results are not satisfactory in various fields. Hence, many researchers have enhanced the LBP in the specific domain, and achieved lots of efficient results. Clearly it is necessary to summarize variants of LBP methods, especially which are used in texture analysis and face recognition applications

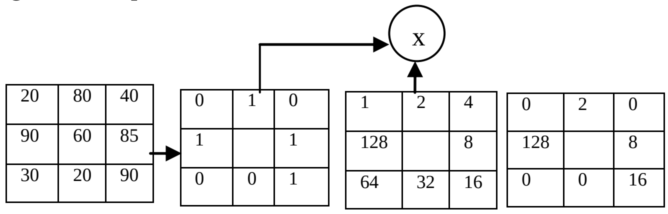
The rest of the paper is organized as follows. Section 1 briefly reviews about local binary pattern. Section2 presents different existing improved LBP methods to extract the texture features. Section 3 presents concludes the paper.

II. LOCAL BINARY PATTERN

The initial LBP method is used to extract a texture feature which is proposed by Ojala et al. [1] .It gives the local contrast measure of image. Initially LBP is defined in a neighborhood of eight pixels, and gray value center pixel. The Calculation process of original LBP is shown in Fig. 1.The neighborhood pixels are represented by $g_p$where$p$= (0,...,7).The center pixel is represented by g_c. P represents the number of neighborhood pixels that is 8.The original LBP is defined as

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

Where $g_c, g_p (p = 0, \ldots \ldots P-1)$ are intensity values of central pixel and neighboring pixels.$P$is the number of neighborhood pixels



Binary Pattern-01011001

LBP=0+2+0+8+16+0+0+128= 154

Fig.1.The Calculation Process of Original LBP

The original LBP has a disadvantage i.e. it is not able to extract the texture features in large size and structure. So Ojala et al. [4] has changed the LBP.In this modified method the neighboring pixels are taken in circular form with center pixel.The process, which is used to take the neighboring pixels in circular form, is described in [4] .The conventional LBP is as

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

Where $g_c, g_p (p = 0, \ldots \ldots P-1)$ are intensity values of central pixel and neighboring pixels. $P$is the number of neighborhood pixels. This method produces 2^P patterns. If P is increased, the binary patterns are raised.to reduce these number of patterns Ojala et al.[4] proposed “Uniform Patterns”. The ULBP is described as

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

Where g_c, g_p, P are described in Eq.(2).Where U (LBP p, r) is <=2 then that pattern is called Uniform. The example to uniform patterns, 00000000 (zero bitwise change), 01110000 (two bitwise changes) while 11001001 (four bitwise changes) and 0101001 (six bitwise changes) are not uniform patterns. This method contains binary patterns of eight neighboring pixels 56 from the original 256.

For achieving rotation invariance a locally invariant pattern [4] is defined as follows

$$LBP^{ri}_{P,R} = min\left(ROR\left(LBP^{ri}_{P,R}, i\right) i = 0,1, \ldots P-1\right) \quad (4)$$

The rotation invariance of LBP can also be combined with uniform patterns. Rotation invariant and uniform local binary pattern [4] is defined as

$$LBP^{riu2}_{P,R} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c), & if U\left(LBP_{P,R} \leq 2\right) \\ P+1, & otherwise \end{cases} \quad (5)$$

Where g_c, g_p, P are described in Eq.(2). The LBP gives great success in early application experiments but practical results are not satisfactory for some fields so, researchers have proposed different improved methods of LBP for extraction of texture features.

III. IMPROVED LBP METHODS

A. Joint Local Binary Pattern

Zhiping Dan et al.[5] proposed a joint local binary pattern method for extraction of texture features. JLBP gives good success in experimental result with multiple scales in gray values. But the LBP method did not describe the best of the patterns in different scales, and also describes simple structure. Therefore Joint LBP with two scales of the pixel(x, y) is defined as

$$JLBP_{S_1,S_2}(x,y) = \left(LBP_{S_1}(x,y), LBP_{S_2}(x,y)\right) \quad (6)$$

Where (x, y) coordinates of a pixel, S_1= (P1, R1) and S_2= (P2, R2) stands for two groups of various scale parameters (P,R). Likewise the rotation invariant uniform joint local binary pattern (JLBP^{riu2}) with two scales can also be defined as

$$JLBP^{riu2}_{S_1,S_2}(x,y) = \left(LBP^{riu2}_{S_1}(x,y) LBP^{riu2}_{S_2}(x,y)\right) \quad (7)$$

B. Local Weber- like response

In LBP method signed difference pattern is same for different structures of image.It can be illustrated in the Fig.2 .

40	65	60
72	75	71
30	72	73

→

65	65	64
70	70	70
30	72	73

$LBP_{8,1} = 00000000 \quad LBP_{8,1} = 00000000$

Fig.2. same LBP value for two different local regions

So, to overcome this drawback Zhipingdan et al. [5] proposed a Weber's law. This method considers the local grey value difference and its original gray value. The Local Weber-Like response defined as

$$W_{P,R} = arctan\left(\frac{1}{P}\sum_{p=0}^{P-1}\frac{|g_p - g_c|}{g_c + \Delta}\right) (8)$$

Where g_c, g_p, P are described in Eq.(2).$|g_p - g_c|$is absolution of $g_p - g_c$and Δ is a little value. It avoids dividing by zero. The arctan(.) function prevents the response from being infinitely great when $g_c$zero.Now iscombining the rotation-invariant uniform joint local binary patterns with theWeber-Like response. If the texture image sizes are MxN, then the final histogram of JLBPW^{riu2}with two scales (s1,s2) is calculated as

$$H(u,v) = \sum_{x=1}^{M}\sum_{y=1}^{N} w\left(JLBP^{riu2}_{S_1,S_2}(x,y), u, v\right) \quad (9)$$

Where

$$w\left(JLBP^{riu2}_{S_1,S_2}(x,y), u, v\right) = \begin{cases} W_{S_1} + W_{S_2,} & JLBP^{riu2}_{S_1,S_2}(x,y)=(u,v) \\ 0\ , & otherwise \end{cases} \quad (10)$$

C. Local Ternary Pattern

Local Ternary Pattern: In LBP[1] method the intensity of the central pixel is used directly as threshold. So it is sensitive to noise, mainly in the near uniform image regions. A small change of the central pixel (75-70) greatly changes the LBP code is shown in Fig.3. To overcome this problem, Tan and Triggs [6] proposed a LTP which is extended to original LBP. The LTP operator is defined as

$$LTP_{P,R} = \sum_{p=0}^{P-1} s\left(g_p - g_c\right) 2^p, \quad s(x) = \begin{cases} 1\ , & x \geq t \\ 0, & |x| < t \\ -1\ , & x < -t \end{cases} \quad (11)$$

Where g_c, g_p, P are described in Eq.(1) and t is a threshold, this value is defined by user. By using threshold t conventional 2-values (0,1) LBP code is extended to 3-valued (-1, 0,1) ternary code is shown in Fig.3. The threshold t is specified by user. Soit is, robust to noise but it is no longer invariant to monotonic gray scale transformation.

100	100	100
100	140	100
100	100	100

noise 75-70

100	100	100
100	240	100
100	100	100

LBPcode: 00000000 LBPcode: 00011101

Fig.3. Example for LBP is noise sensitive

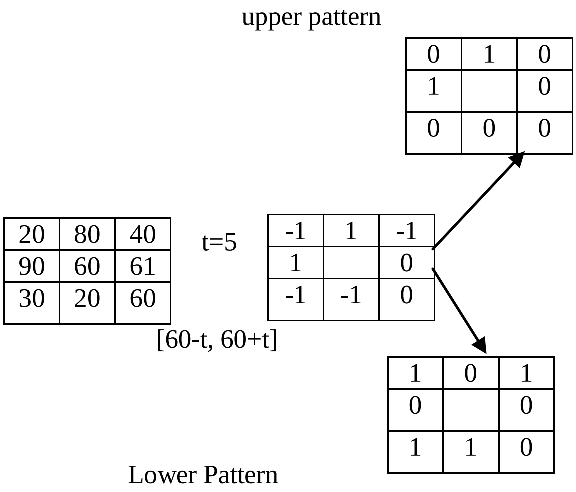


Fig.4. Example for LTP Process

In Fig.4 .Ternary code is (-1)1(-1)00(-1)(-1)1, the Binary code for upper pattern is 01000001, the binary code for lower pattern is 10100110.

D. Completed Local Binary Pattern

One of disadvantage of LBP is that many various structural patterns may have the identical LBP code which is shown in fig.2. To overcome this problem, Guo et al [7] proposed the method of CLBP. In CLBP, the image local differences are divided in to two complementary components. They are signs (s_p) and the magnitudes (m_p) respectively.

$$s_p = s\left(g_p - g_c\right) \qquad (12)$$

$$m_p = \left|g_p - g_c\right| \qquad (13)$$

These two operators named CLBP_Sign(CLBP_S) and CLBP_Magnitude(CLBP_M). Here CLBP_S is identical to the conventional LBP. CLBP_M measures the local variance of magnitude. The CLBP_M can be defined as

$$CLBP\_M_{P,R} = \sum_{p=0}^{P-1} s\left(m_p - c\right) 2^p, \quad s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \qquad (14)$$

Where g_c, g_p, P are described in Eq.(2) and c is the mean value of$m_p$of the whole image. Guo et al [7] observed that the center pixel, also has discriminative information. So they defined an operator CLBP_C to extract the local central information CLBP_C is defined as

$$CLBP\_C_{P,R} = s(g_c - c_l) \qquad (15)$$

Where threshold c_l is the mean gray level of the whole image. By combining the these three operators CLBP_S,CLBP_M,CLBP_C represented as CLBP_S/M/C which is give better progress, but CLBP solves some confusion of various patterns, not all of the patterns can be distinguished.shown infig.5 shows this drawback . That is two patterns have same sign code and magnitude code, but their local structures are different. It is also sensitive to noise because the value of pixel is used as threshold.

a

50	50	50
50	80	50
50	50	50

b

60	50	40
50	80	10
40	10	10

Sign code:00000000 Sign code:00000000

Magnitude code:11111111 Magnitude code:11111111

Fig.5. dissimilar patterns may have equal CLBP code

E. Robust local binary pattern

Yang Zhao et al[8] proposed a RLBP. It inherits the advantages of LTP and CLBP, but can overcome their disadvantages. They defined Average local gray level (ALG) as follows

$$ALG = \frac{\sum_{i=1}^{8} g_p + g_c}{9} \qquad (16)$$

Where g_c represents the intensity of the center pixel and g_p(0------8) denoted the gray value of neighbor pixel. The ALG is taken as threshold which is insensitive to noise. Now LBP process is applied by using ALG as the threshold named Robust Local Binary Pattern (RLBP).
RLBP is defined as

$$RLBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - ALG_c)2^p = \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + g_c}{9}\right)2^p \quad (17)$$

Where $g_c$denotes the intensity value of the center pixel and g_p(p=0-----P-1) represents the gray value of the neighbor pixel on a circle of radius R, P is the total number of the neighbors, and g_{ci}(i=0, -----8) denotes the gray value of the neighbor pixel ofg_c.RLBP is insensitive to noise and two various patterns with the same LBP code may have various RLBP code. Since the neighbors of each neighbor pixel are also considered. ALG ignores the specific information of the center pixel which is also needed in some times. So Yang Zhao et al [8] proposed a Weighted Local Gray Level (WLG). It is defined as

$$WLG = \frac{\sum_{i=1}^{8} g_i + \alpha g}{8 + \alpha} \qquad (18)$$

Where$g$ and g_i are defined in Eq.(16) and α is a parameter set by user. If α=1 then WLG is equivalentto ALG. RLBP is defined as

$$RLBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - WLG_c)2^p = \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} - \alpha g_c}{8 + \alpha}\right)2^p \quad (19)$$

They observed that RLBP is insensitive to noise when α is takes as 1, but it will have more sensitive to noise if α >8.

F. Complete robust local binary pattern

Yang Zhao et al[8] proposed a CRLBP. The RLBP extracts only the gray level information of both local neighbor set and individual pixel. But CRLBP inherits the merits of RLBP and also measures the local variance of WLG, the local central information. RLBP_Magnitude(RLBP_M) measures the local variance of WLG. They define RLBP_M as follows

$$RLBP_{M_{P,R}} = \sum_{p=0}^{P-1} s\left(m_p - c\right) 2^p \quad (20)$$

Where

$$m_p = \left|WLG_p - WLG_c\right| = \left|\frac{\sum_{i=1}^{8} g_{pi} + \alpha g_p}{8+\alpha} - \frac{\sum_{i=1}^{8} g_{ci} + \alpha g_{pc}}{8+\alpha}\right| \quad (21)$$

Where g_p, g_c, g_{ci} are defined in Eq. (17), g_{pi}(i=0---,8) represens the gray value of the neighbor pixel of g_p, and parameter of WLG is α. Threshold c is the average value of mp of the whole image. The center pixel express the image central gray level, also has discriminative information. Thus they also defined an operator named RLBP_Center(RLBP_C) to extract the local central information as follows:

$$RLBP\_C_{P,R} = s(WLG_c - c_l) \quad (22)$$

Where threshold c_l is mean local gray level of the whole image. These Three operators RLBP, RLBP_M, RLBP_C are combined bytheprocess, which is described in [7], and represented as CRLBP.

G. Complete local binary count

Y.Zhao et al [9] proposed a CLBC Method. It is similar to CLBP [7] method. CLBP is not totally rotation invariant to label the pattern which is shown in Fig.6. So in CLBC method the authors just counted the number of value 1's of the threshold step instead of encoding them. TheCLBC_Sign (CLBP_S) is defined as

$$CLBP\_S_{P,R} = \sum_{p=0}^{P-1} s\left(g_p - g_c\right), \quad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (23)$$

Where g_c, g_p, P are described in Eqn.(2). They are also defined CLBPC_M, CLBP_C. These three are combined into joint or hybrid distributions. These are used to extract the texture features which are rotation invariant.

$$CLBPC\_M_{P,R} = \sum_{p=0}^{P-1} s\left(m_p - c\right), s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (24)$$

$$CLBPC\_C_{P,R} = s(g_c - c_l) \quad (25)$$

50	50	50
50	80	50
50	50	50

rotate30^0

50	50	50
50	80	50
50	50	50

rotation invariant of LBP code:00001011

rotation invariant of LBP code:00000111

Fig.6. after rotation, rotation invariant codes in LBP may not stable.

H. Complete local ternary pattern

Taha.Rassem et al[10] proposed a method CLTP, which is insensitive to noise and gives the accuracy in result of texture classification. It is similar to CLBP. In CLTP, the local difference of the image is divided into two sign complementary components and two magnitude complementary components.

$$s_p^{upper} = s\left(g_c - (g_c + t)\right), s_p^{lower} = s\left(g_c - (g_c - t)\right) \quad (26)$$

$$m_p^{upper} = \left|g_c - (g_c + t)\right|, m_p^{lower} = \left|g_c - (g_c - t)\right| \quad (27)$$

Where g_c, g_p, P are described in Eqn.(2).

$CLTP\_S_{P,R}^{upper}$ is defined as

$$CLTP\_S_{P,R}^{upper} = \sum_{p}^{P-1} s\left(g_c - (g_c + t)\right)2^p,$$

$$s_p^{upper} = \begin{cases} 1, & g_p \geq g_c + t \\ 0, & otherwise \end{cases} \quad (28)$$

$$CLTP\_S_{P,R}^{lower} = \sum_{p}^{P-1} s\left(g_c - (g_c - t)\right)2^p,$$

$$s_p^{lower} = \begin{cases} 1, & g_p < g_c - t \\ 0, & otherwise \end{cases} \quad (29)$$

$CLTP\_S_{P,R}$ is the concatenation of the $CLTP\_S_{P,R}^{upper}$ *and* $CLTP\_S_{P,R}^{lower}$. It is defined as

$$CLTP\_S_{P,R} = \left[CLTP\_S_{P,R}^{upper}, CLTP\_S_{P,R}^{lower}\right] \quad (30)$$

$CLTP\_M_{P,R}$ is defined with magnitude complementary components as

$CLTP\_M_{P,R}^{upper}$ is defined as

$$CLTP\_M_{P,R}^{upper} = \sum_{p}^{P-1} t\left(m_p^{upper}, c\right)2^p,$$

$$t\left(m_p^{upper}, c\right) = \begin{cases} 1, & \left|g_p - (g_c + t)\right| \geq c \\ 0, & \left|g_p - (g_c + t)\right| < c \end{cases} \quad (31)$$

$CLTP\_M_{P,R}^{lower}$ is defined as

$$\mathrm{CLTP\_M_{P,R}^{lower}} = \sum_{\mathrm{p}}^{\mathrm{P-1}} \mathrm{t}\left(\mathrm{m_p^{lower}}, \mathrm{c}\right)2^{\mathrm{p}},$$

$$\mathrm{t}\left(\mathrm{m_p^{lower}}, \mathrm{c}\right) = \begin{cases} 1, & \left|\mathrm{g_p} - (\mathrm{g_c} - \mathrm{t})\right| \geq \mathrm{c} \\ 0, & \left|\mathrm{g_p} - (\mathrm{g_c} - \mathrm{t})\right| < c \end{cases} \quad (32)$$

$\mathrm{CLTP\_M_{P,R}}$ is constructed with the concatenation of $\mathrm{CLTP\_M_{P,R}^{upper}}$ and $\mathrm{CLTP\_M_{P,R}^{lower}}$ .It is defined as

$$\mathrm{CLTP\_M_{P,R}} = \left[\mathrm{CLTP\_M_{P,R}^{upper}}, \mathrm{CLTP\_M_{P,R}^{lower}}\right] \qquad (33)$$

Where g_c, g_p, P are described in Eq.(2),Eqn.(16).

$\mathrm{CLTP\_C_{P,R}}$ is constructed with the concatenation of $\mathrm{CLTP\_C_{P,R}^{upper}}$ and $\mathrm{CLTP\_C_{P,R}^{lower}}$ .It is defined as

$$\mathrm{CLTP\_C_{P,R}} = \left[\mathrm{CLTP\_C_{P,R}^{upper}}, \mathrm{CLTP\_C_{P,R}^{lower}}\right]$$

Where $CLTP_{M_{P,R}}^{upper} = t(g_c^{upper}, c_l)$,

$$CLTP_{M_{P,R}}^{lower} = t(g_c^{lower}, c_l), \qquad (34)$$

Where $g_c^{upper} = g_c + t$, $g_c^{lower} = g_c - t$, $\mathrm{c_l}$ is mean gray values of whole image.

Finally, operator histogram CLTP is constructed by the combination of these three operators $\mathrm{CLTP\_S_{P,R}}$, $\mathrm{CLTP\ M_{P,R}}$, $\mathrm{CLTP\_C_{P,R}}$ into joint or hybrid distributions similar tothe CLBP and CLBC [7, 9], respectively.

IV. CONCLUSION

LBP methodology is easy and less computational complexity. It also has gray scale invariance, rotation invariant and other significant advantages.It is used in many applications such as texture classification, texture analysis, face analysis, biological and medical image analysis.

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