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;Texture 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

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

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

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

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

Where \( g_c, g_p \) \((p = 0, ..., P - 1)\) 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

\[
U(LBP_{p,r}) = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)|
\]

Where \( g_c, g_p, P \) are described in Eq.(2). Where \( U \) (LBP p, r) is \( \leq 2 \) then that pattern is called Uniform. The example to uniform patterns, 00000000 (zero bitwise change), 01110000 (two bitwise changes) while 11010101 (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
$LBP_{P,R}^{ri} = \min\left\{ ROR\left(LBP_{P,R}^{ri}, i\right) \right\}$ \(i = 0, 1, \ldots P - 1\) \(4\)

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

\[LBP_{P,R}^{riu2} = \left\{ \sum_{p=0}^{P-1} s\left(g_p - g_r\right), \quad i\ R\ U\ \left(LBP_{P,R} \leq 2\right) \right\}
\]

Where \(g_r, g_p, P\) 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

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

Where (x, y) coordinates of a pixel, \(S_1 = (P_1, R_1)\) and \(S_2 = (P_2, R_2)\) 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

$$JLBP_{S_1, S_2}^{riu2}(x, y) = \left( LBP_{S_1}^{riu2}(x, y), LBP_{S_2}^{riu2}(x, y) \right)$$ \(7\)

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.

\[
\begin{array}{ccc}
40 & 65 & 60 \\
72 & 75 & 71 \\
30 & 72 & 73 \\
\end{array}
\]

$LBP_{0,1}^{000000000}$ $LBP_{0,1}^{000000001}$

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

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

Where \(g_r, g_p, P\) are described in Eq.(2), \(|g_p - g_r|\) is absoluton of \(g_p - g_r\) and \(\Delta\) is a little value. It avoids dividing by zero. The \(\arctan(.)\) function prevents the response from being infinitely great when \(g_r\) zero. Now iscombining the rotation-invariant uniform joint local binary patterns with the Weber-Like response. If the texture image sizes are \(MN\), then the final histogram of JLBPW\(riu2\) with two scales \((s_1, s_2)\) is calculated as

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

Where

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

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

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

Where \(g_r, g_p, P\) 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. So it is, robust to noise but it is no longer invariant to monotonic gray scale transformation.

\[
\begin{array}{ccc}
100 & 100 & 100 \\
100 & 140 & 100 \\
100 & 100 & 100 \\
\end{array}
\]

noise 75-70

\[
\begin{array}{ccc}
100 & 240 & 100 \\
100 & 100 & 100 \\
100 & 100 & 100 \\
\end{array}
\]

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.

$$s_p = \frac{g_p - g_c}{g_c}$$

$$m_p = |g_p - g_c|$$

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

$$CLBP_{M,R} = \sum_{p=0}^{P-1} s(m_p - c) 2^p, \ s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

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

$$CLBP_{C,R} = s(g_c - c_i)$$

Where threshold $c_i$ 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.

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

$$ALG = \frac{\sum_{i=0}^{8} g_i}{9}$$

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

$$RLBP_{p,R} = \sum_{p=0}^{P-1} s(g_p - ALG_c) 2^p = \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=0}^{8} g_i}{9} \right) 2^p$$

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

$$CLBP_{C,R} = s(g_c - c_i)$$

Where threshold $c_i$ 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.
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:

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

Where

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

Where $g_{pi}, g_{ci}$ are defined in Eq. (17), $g_{pi}(i=0\ldots8)$ represents the gray value of the neighbor pixel of $g_p$, and parameter of WLG is $\alpha$. 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:

$$RLBP_{C,R} = s(WLG_c - c_i)$$

Where threshold $c_i$ is mean local gray level of the whole image. These Three operators RLBP, RLBP_M, RLBP_C are combined by the process, 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

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

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.

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

$$CLBPC_{C,R} = s(g_c - c_i)$$

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).

$$CLTP_{S,R}^{upper} = \sum_{p=0}^{P-1} s\left(g_c - (g_c + t)\right) 2^p,$$

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

$$CLTP_{S,R}^{lower} = \sum_{p=0}^{P-1} s\left(g_c - (g_c - t)\right) 2^p,$$

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

$CLTP_{S,R}$ is the concatenation of the CLTP $S_{R}^{upper}$ and $CLTP_{S,R}^{lower}$.

It is defined as

$$CLTP_{S,R} = [CLTP_{S,R}^{upper}, CLTP_{S,R}^{lower}]$$

$CLTP_{M,R}$ is defined with magnitude complementary components as

$$CLTP_{M,R}^{upper} = \sum_{p=0}^{P-1} t\left(m_p^{upper}, c\right) 2^p,$$

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

$$CLTP_{M,R}^{lower}$$ is defined as

$$CLTP_{M,R}^{lower} = \sum_{p=0}^{P-1} t\left(m_p^{lower}, c\right) 2^p,$$

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

$CLTP_{M,R}$ is constructed with the concatenation of $CLTP_{M,R}^{upper}$ and $CLTP_{M,R}^{lower}$. It is defined as
\[ \text{CLTP}_{M,P,R} = [\text{CLTP}_{M_{P,R}}^{\text{upper}}, \text{CLTP}_{M_{P,R}}^{\text{lower}}] \]  \hspace{1cm} (33)

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

CLTP_{C,P,R} is constructed with the concatenation of CLTP_{C_{P,R}}^{\text{upper}} and CLTP_{C_{P,R}}^{\text{lower}}. It is defined as

\[ \text{CLTP}_{C_{P,R}} = [\text{CLTP}_{C_{P,R}}^{\text{upper}}, \text{CLTP}_{C_{P,R}}^{\text{lower}}] \]

Where \( \text{CLTP}_{M_{P,R}}^{\text{upper}} = t(g_c^{\text{upper}}, c_i) \),
\( \text{CLTP}_{M_{P,R}}^{\text{lower}} = t(g_c^{\text{lower}}, c_i) \), \hspace{1cm} (34)

Where \( g_c^{\text{upper}} = g_c + t, g_c^{\text{lower}} = g_c - t, c_i \) is mean gray values of whole image.

Finally, operator histogram CLTP is constructed by the combination of these three operators CLTP_{S_{P,R}}, CLTP_{M_{P,R}}, CLTP_{C_{P,R}} into joint or hybrid distributions similar to the 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.

REFERENCES