Research and Perspective on Local Binary Pattern

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Research and Perspective on Local Binary Pattern

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Abstract In view of the theoretical and practical value of local binary pattern (LBP), the various LBP methods in texture analysis and classification, face analysis and recognition, and other detection applications are reviewed. Firstly, the principle of LBP method is briefly discussed, which mainly analyses the threshold operation, the uniform pattern and rotation invariant pattern in LBP method. Secondly, the texture analysis and classification of the LBP method, face analysis and recognition of the LBP method and other detection applications of the LBP method are particular combed and commented. Finally, the existing important problems of the LBP method are analyzed and the future for the LBP method is pointed out.

Key words Local binary pattern, feature extraction, texture analysis, face analysis, object detection

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Representation of the image feature is an important basic work in computer vision and digital image processing. Among the commonly used color feature, texture feature, shape feature and spatial relationship feature, texture feature plays a very important role on the application analysis of natural images. Therefore, how to effectively obtain texture feature information is an active research topic in image feature extraction.

In recent years, local binary pattern (LBP)[1−4] feature extraction method has made a remarkable progress in texture analysis and face recognition applications, and has sprung up many improvement methods. LBP method is not only relatively simple and with low computation complexity, but also has the properties of rotational invariance, gray scale invariance and other significant advantages. Therefore, LBP is widely used in image matching, pedestrian and car target detection and tracking, biological and medical image analysis[5].

Despite the great success of LBP in early applications, its practical results are not satisfactory in different fields. Hence, many researchers have improved the LBP in the specific domains, and achieved lots of significant results. Obviously, it is necessary to summarize variants of LBP methods, especially in texture analysis and face recognition applications, and there exists a need to describe the remaining significant issues of LBP and research directions of the future.

The rest of the paper is organized as follows. Section 1 briefly reviews local binary pattern. Section 2 presents LBP methods for texture analysis and classification. Section 3 presents LBP methods for face analysis and recognition. Section 4 reports LBP methods for other detection applications. Section 5 discusses the remaining issues of LBP and Section 6 concludes the paper.

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1 Brief review of local binary pattern

LBP is a kind of gray level within the scope of the texture measure, which is initially proposed by Ojala et al.[1] to support the local contrast measure of image. LBP is initially defined in a neighborhood of eight pixels, and the gray value of center pixel is set as a threshold. All neighbors that have values higher than or equal to the value of the central pixel are given a value of 1, otherwise they are set as 0. The values after the thresholding (namely 0 or l) will respectively multiply with the corresponding pixel weight, and their additive result is the LBP value. The calculation principle of original LBP is shown in Fig. 1.

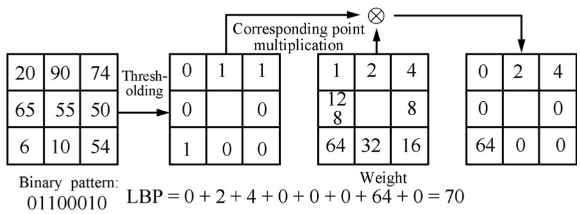

Fig. 1 The calculation principle of original LBP

Since the original LBP is unable to extract texture features in large size and structure, Ojala[4] has modified the LBP and formulated the completed theory to improve the limitations. In a gray image, a local neighborhood is defined as a set of sampling points evenly spaced on a circle, which is centered at the pixel to be labeled. Fig. 2 shows some examples of the LBP operator, where the notation (P, R) denotes a neighborhood of P sampling points on a circle of radius R. T is the local texture feature of neighborhood, namely:

$$T = t\left(g_c, g_0, \cdots, g_{p-1}\right) \tag{1}$$

where g_c and g_i ($i = 0, \cdots, P{-}1$) are, respectively, gray-level values of the central pixel and P surrounding pixels in the circular neighborhood with radius R. t is a function for texture.

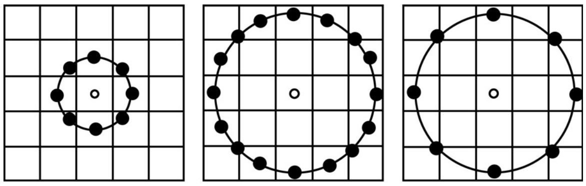

Fig. 2 The circular neighborhood for different P and R

With the increase of the radius, the correlation among the pixels gradually reduces, therefore, most of the texture information can be obtained in the small neighborhood. Without losing information, the gray value of the center pixel can be subtracted from the neighborhood. Hence, the local texture feature is shown:

$$T = t\left(g_c, g_0 - g_c, \cdots, g_{p-1} - g_c\right) \tag{2}$$

Assuming that the differences are independent of g_c, which allows us to factorize (2):

$$T \approx t\left(g_c\right) t\left(g_0 - g_c, \cdots, g_{p-1} - g_c\right) \tag{3}$$

Since the distribution $t(g_c)$ in (3) describes the overall luminance of the image (i.e., it is unrelated to local image texture), it does not provide useful information for local texture analysis. Hence, much of the information in the original joint gray level distribution (1) about the textural characteristics is conveyed by the joint difference distribution:

$$T \approx t\left(g_0 - g_c, \cdots, g_{p-1} - g_c\right) \tag{4}$$

Although texture in (4) is not affected by changes in the gray value, the texture feature will be changed when the pixel values enlarge or shrink the same multiples. In order to make the texture definition avoid the influence of the changes, signed differences are only considered:

$$\begin{aligned} &T \approx t\left(s\left(g_0 - g_c\right), \cdots, s\left(g_{p-1} - g_c,\right)\right), \\ &s\left(x\right) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \end{aligned} \tag{5}$$

Function $s(g_i - g_c)$ multiplied by the factor 2^i, then the only LBP value of local texture feature will be obtained:

$$LBP_{P,R} = \sum_{i=0}^{P-1} s\left(g_i - g_c\right) 2^i \tag{6}$$

In the experimental process, different initial position of unsigned binary number will produce 2^P patterns for corresponding $LBP_{P,R}$. Obviously, as the neighborhood sampling point number increases, the binary pattern species rapidly rise. So many patterns are adverse for texture extraction and texture classification. To solve this issue, Ojala[4] proposed "Uniform patterns". In a cyclic operation of the binary number, the patterns that at most only have two bitwise changes are denoted "Uniform patterns". For example: 00000000 (zero bitwise change), 01110000 (two bitwise changes), and 11001111 (two bitwise changes) are uniform patterns, while 11001001 (four bitwise changes) and 01010010 (six bitwise changes) are not uniform patterns. To check some patterns are uniform patterns or not, a simple method is shown as follows:

$$\begin{aligned} U\left(LBP_{P,R}\right) = &\left|s\left(g_{p-1} - g_c\right) - s\left(g_0 - g_c\right)\right| + \\ &\sum_{p=1}^{P-1} \left|s\left(g_p - g_c\right) - s\left(g_{p-1} - g_c\right)\right| \end{aligned} \tag{7}$$

When $U\left(LBP_{P,R}\right)$ is less than or equal to 2, the pattern is called uniform pattern, denoted as $LBP_{P,R}^{u2}$. While other patterns are called hybrid patterns. Hence the species of improved binary pattern will greatly decrease, for example: binary pattern of eight sampling points is reduced to 58 from the original 256.

To achieve rotation invariance, a locally rotation invariant pattern is defined as follows:

$$LBP_{P,R}^{ri} = \min\left(ROR\left(LBP_{P,R}^{ri}, i\right) i = 0, 1, \cdots, P-1\right) \tag{8}$$

where $ROR(x,\ i)$ is rotating function. By introducing the definition of rotation invariance, LBP not only has prominent performance for image rotation, but also has less patterns. In addition, the rotation invariance of LBP can also be combined with uniform patterns:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum\limits_{p=0}^{P-1} s\left(g_p - g_c\right), & \text{if } U\left(LBP_{P,R}\right) \leq 2 \\ P+1, & \text{otherwise} \end{cases} \tag{9}$$

where $U\left(LBP_{P,R}\right)$ is calculated by (7), superscript $riu2$ means rotation invariant "uniform" patterns.

Despite the great success of LBP in early application experiments, its practical results are not satisfactory in different fields. Hence, many researchers have improved the LBP for the specific application (especially in texture analysis and face recognition), and achieved lots of significant results. The reviews for texture analysis and classification, face analysis and recognition and other detection applications of LBP method are respectively introduced in detail below.

2 LBP methods in texture analysis and classification

Because LBP method is mainly used to describe texture feature information, the applications of the early studies have focused on the texture analysis and classification processing. Several kinds of influential LBP improvement methods are discussed and analyzed as follows.

2.1 Median binary pattern (MBP)

Hafiane et al.[6] proposed the median binary pattern (MBP) method for texture classification, which seeks to derive the localized binary pattern by thresholding the pixels against their median value over a 3 × 3 neighborhood. The central pixel is included in this filtering process, therefore 2^9 possible structures are obtained. MBP is defined as follows:

$$MBP = \sum_{i=1}^{L} f(g_i) \times 2^i f(g_i) = \begin{cases} 1, & \text{if } g_i \geq Med \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where L is the number of neighbors and g_i is the intensity value.

MBP captures the contrast between two intensity ranges which also impacts the local structure. These patterns form the basic element of texture. However, the scale changes can influence local structures, thus impact the MBP descriptor. To reduce this affect, the image is decomposed into several frequency ranges by sub sampling method. These subimages can capture relationship among pixels, which are not immediate neighbors. Although a median is invariant under rotation, the coding used to label the pattern is not invariant to rotation.

2.2 Adaptive LBP (ALBP)

Guo et al.[7] exploited the adaptive LBP (ALBP) method for texture classification, which introduces the directional statistical information. Specifically, the mean and standard deviation of the local absolute difference are extracted to improve the classification efficiency of LBP. Three different directional statistical features are calculated: the mean μ_p and standard deviation σ_p of local difference, and the weight of minimizing the directional difference w_p. Adaptive LBP is formulated as follows:

$$ALBP = \sum_{p=0}^{P-1} s(g_p w_p - g_c) 2^p \tag{11}$$

where $w_p = \boldsymbol{g}_p^{\mathrm{T}} \boldsymbol{g}_c / (\boldsymbol{g}_p^{\mathrm{T}} \boldsymbol{g}_p), \boldsymbol{g}_c = [g_c(1,1);\ g_c(1,2); \cdots;\ g_c(N,M)]$ is a column vector containing all the possible $g_c(i,j)$ pixels. $\boldsymbol{g}_p = [g_p(1,1); g_p(1,2); \cdots; g_p(N,M)]$ is the corresponding vector for all $g_p(i,j)$ pixels. $\boldsymbol{g}_p^{\mathrm{T}}$ is the transposition of $\boldsymbol{g}_p$.

The mean μ_p and standard deviation σ_p of local difference are as follows:

$$\mu_p = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} |g_c(i,j) - g_p(i,j) w_p|}{M \times N} \tag{12}$$

$$\sigma_p = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M} \frac{(|g_c(i,j) - g_p(i,j) w_p| - \mu_p)^2}{M \times N}} \tag{13}$$

Experiments on CUReT[8] texture database show that the texture feature extraction and classification scheme of ALBP can significantly improve the classification accuracy of LBP. However, the robustness is not inspected in matching as it contained noisy texture image.

2.3 Completed LBP (CLBP)

Guo et al.[9] proposed the completed LBP (CLBP) method for texture classification, which accounts for the reason that the simple LBP code could convey so much discriminant information of the local structure. Further more, CLBP designs a scheme to effectively represent the missing information in the LBP style so that better texture classification can be achieved. A local region is represented by its center pixel and a local difference sign-magnitude transform (LDSMT), and three operators, namely CLBP-Center (CLBP_C), CLBP-Sign (CLBP_S) and CLBP-Magnitude (CLBP_M), are proposed to code them. The difference between central pixel and spaced neighbours can be calculated by d_p : $d_p = g_p - g_c$, d_p can be further decomposed into two components:

$$d_p = s_p * m_p,\ \ s_p = \mathrm{sign}(d_p), m_p = |d_p| \tag{14}$$

where $s_p = \begin{cases} 1, d_p \geq 0 \\ -1, d_p < 0 \end{cases}$, s_p is the sign of d_p and m_p is the magnitude of d_p. It is clearly seen that the original LBP uses only the sign vector to code the local pattern ("-1" is coded as "0"). CLBP_M operator is defined as

$$\begin{aligned} &CLBP\_M_{P,R} = \sum_{p=0}^{P-1} t(m_p, c) 2^p, \\ &t(x,c) = \begin{cases} 1, & x \geq c \\ 0, & x < c \end{cases} \end{aligned} \tag{15}$$

where c is a threshold to be determined adaptively, it is set as the mean value of the whole image in practice. CLBP_C operator is defined as

$$CLBP\_C_{P,R} = t(g_c, c_I) \tag{16}$$

where t is defined in CLBP_M and the threshold c_I is set as the average gray level of the whole image.

CLBP demonstrated that the sign component is more important than the magnitude component in preserving the local difference information, which can explain why the CLBP_S (i.e., conventional LBP) features are more effective than the CLBP_M features. However, CLBP has not given a scheme to solve the issue that LBP is sensitive to gaussian noise.

2.4 LBP variance (LBPV)

In LBP method, VAR is the supplement for LBP. However VAR is a series of continuous values, and needed to carry out quantitative treatment, and this process has great influence on the result of the experiment. To overcome the drawback, Guo et al.[10] exploited the LBP variance (LBPV) method for texture classification, which treated the variance of each point as weight of code value, and then accumulated the histogram. The definition of LBPV is as follows:

$$LBPV = \sum_{i=1}^{N}\sum_{j=1}^{M} w(LBP_{P,R}(i,j), k,), \quad k \in [0, K] \tag{17}$$

$$w\left(LBP_{P,R}\left(i,j\right),k\right)=\begin{cases} VAR_{P,R}\left(i,j\right), \\ \quad LBP_{P,R}\left(i,j\right)=k \\ 0, \quad \text{otherwise}\end{cases} \tag{18}$$

The value of VAR represents the regional change, so larger VAR value means larger contribution for distinction of the area and bigger corresponding coding weight. LBPV does not need any quantization and it is totally training-free. However, LBPV does not give a scheme to solve the issue that LBP is sensitive to gaussian noise and affine transformation.

2.5 Bayesian LBP (BLBP)

The stochastic nature of image formation is usually disregarded by LBP methods leading to inaccuracy and sensitivity to the illumination changes and noise. Therefore, He et al.[11] proposed a novel Bayesian LBP (BLBP) operator to deal with above issue. BLBP models the label acquired from filter responses as a stochastic process, and embeds a Markov random field (MRF) in the label space. The labeling procedure is then treated as a joint optimization process under a criterion of maximum a posteriori (MAP). Finally, a histogram estimating the probability density of the labels is used as a descriptor. Labeling process of BLBP is shown in Fig. 3. To analyze and compare the performance in a unified way, a filtering, labeling and statistics (FLS) framework is developed, whose calculation principle is as shown in Fig. 4.

Although BLBP method achieved excellent experimental effect on Brodatz[12] database, alternative smoothing terms and learning parameter values require further study.

2.6 Dominant LBP (DLBP)

Liao et al.[13] exploited the dominant LBP (DLBP) method of texture classification, which uses the most frequently occurred patterns to capture descriptive textural information. The uniform LBPs effectively capture the fundamental information of textures, while the uniform LBPs are not the dominating patterns in some textures with irregular edges and shapes. DLBP considers the most frequently occurred patterns in a texture image, which is demonstrated that a minimum set of pattern labels that represents around 80 % of the total pattern occurrences in an image. Hence, DLBP effectively captures the image textural information for classification tasks.

Although the DLBP features encapsulate more textural information than the conventional LBP features, they lack the consideration of distant pixel interactions. To replenish the missing information in the DLBP features, an additional features set, i.e., features based on the Gabor filter responses are utilized as the supplement to the DLBP features. DLBP has also been compared with six published texture features (DBWP, RDBWP, TGF, CGF, ACGMRF, and LBP) on Outex[14], Brodatz[12] and CUReT[8] texture image databases.

To compare the experimental results accuracy of above several methods, Table 1 respectively gives the classification accuracy on Brodatz database[12], CUReT database[8] and Outex database[14]. We can not comprehensively evaluate the performance of these methods, since only DLBP obtained the corresponding data from three databases while other methods obtained the data from one or two of the databases. However, in available data: classification precision of ALBP is the lowest in the same CUReT database, while LBPV's results are better than CLBP and DLBP; on the same Outex database, MBP's classification accuracy in "inca" is far lower than other methods, but it has won the best classification accuracy in "Tl84" and "Horizon". In addition, Nanni[15] reviewed the improved LBP methods in texture classification.

2.7 Other methods

As early as in 2000, M*äenpää* et al.[16] used beam search method and uniform patterns method to search the most significant patterns, which can be carried out in a number of ways. Moreover, these two methods demonstrated that a small subset of local patterns can perform better than the whole LBP histogram in problems involving geometric transformation (Tilt) between training and testing images.

Table 1 The classification accuracies for various methods on three databases ("−"indicates no data.) (%)

Method	Parameters	Brodatz database	CUReT database	Outex database			Note
				Inca	Tl84	Horizon	
MBP[6]	−	−	−	47.90	97.30	96.10	KNN = 3
ALBP[7]	$P=8, R=1$	−	57.40	−	−	−	
	$P=16, R=3$	−	67.30	−	−	−	
	$P=24, R=5$	−	65.50	−	−	−	
CLBP[9]	$P=8, R=1$	−	86.67	96.56	90.30	92.29	Average value in CUReT
	$P=16, R=3$	−	87.79	98.72	93.54	93.91	Outex: $R=2$
	$P=24, R=5$	−	85.84	98.93	95.32	94.53	Outex: $R=3$
LBPV[10]	$P=8, R=1$	−	88.23	91.56	76.62	77.01	
	$P=16, R=2$	−	89.77	92.16	87.22	84.86	
	$P=24, R=3$	−	91.09	95.26	91.31	85.04	
BLBP[11]	−	90.77	−	−	−	−	Results of texture retrieval
DLBP[13]	$R=2$	98.49	86.84	97.70	92.10	88.70	
	$R=3$	98.26	83.62	98.10	91.60	87.40	

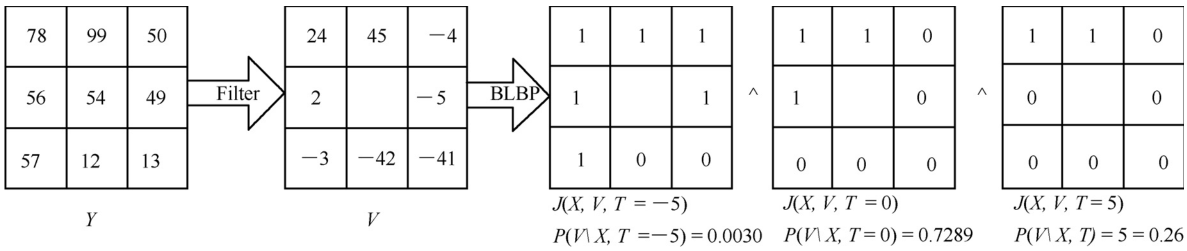

Fig. 3 The labeling procedure of BLBP

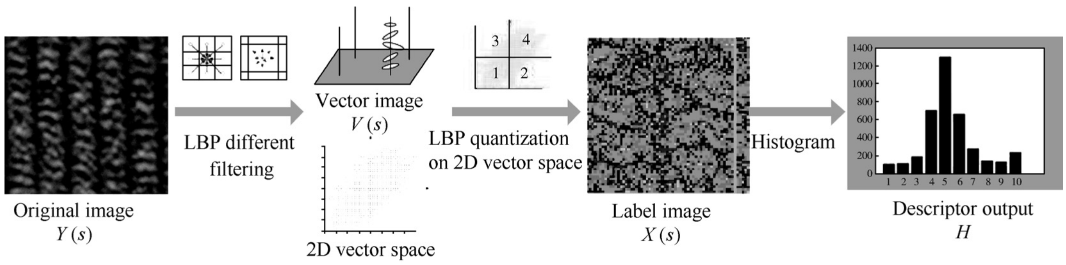

Fig. 4 The FLS framework of image descriptors

Despite the multi-resolution LBP has been shown to be a powerful measure of image texture, its main limitations have been sparse sampling and inability to cope with a large number of different local neighborhoods. Mäenpää et al.[17] presented two techiques (Gaussian low-pass filters and cellular automata) to solve these problems, and achieved excellent classification performance on Outex database[14]. In addition, Raja et al.[18] exploited the multiscale selected local binary features (MSLBF) to deal with the issue of multi-resolution LBP. However, there are two main drawbacks to the pairwise-coupled approach. Firstly, stable results required the same number of features to be used for all classes despite the varying numbers of features required for a given error per class. Secondly, the complete separation between the training of individual binary classifiers does not preclude the possibility of histograms for two classes being similar despite being constructed from completely different features. He et al.[19] proposed the multi-structure local binary pattern (MSLBP) method for texture classification, which extracts three different kinds of structures: isotropic micro structures, isotropic macro structures, and anisotropic macro structures. The performance of MSLBP method is limited by the size of images, since small images are not enough to supply large macro structures.

Ahonen et al.[20] proposed using soft histograms for the LBP operator, which makes the operator more robust to noise and makes its output continuous with respect to input. To increase the robustness of the operator, the thresholding function of LBP is replaced by the two fuzzy membership functions. Possible drawbacks of the proposed operator in comparison to original LBP are increased sensitivity to grayscale changes and computational complexity. Furthermore, Iakovidis et al.[21] extended the LBP method by incorporating fuzzy logic in the representation of local patterns of texture in ultrasound images.

Zhang et al.[22] proposed a novel texture feature extractor, namely Monogenic-LBP (M-LBP). M-LBP integrates the traditional LBP operator with the other two rotation invariant measures: the local phase and the local surface type computed by the 1^{st}-order and 2^{nd} -order Riesz transforms, respectively. M-LBP has the advantage of smaller feature size and faster classification speed, which makes it a more suitable candidate in real applications.

To solve the LBP′s shortcomings (i.e., LBP discards some important texture information and is sensitive to noise), Zhou et al.[23] exploited the extended LBP (ELBP) method for texture analysis, which classifies and combines the "nonuniform" local patterns based on analyzing their structure and occurrence probability. Although three experiments on the Brodatz texture database show the performance improvement of ELBP and its robustness against noise, ELBP could not provide much improvement in a smaller neighborhood. Recently, Liu et al.[24] presents a novel extended LBP (ELBP), in which two different and complementary types of features (i.e., pixel intensities and differences) are extracted from local patches and four descriptors (i.e., CI-LBP, NI-LBP, RD-LBP and AD-LBP) are developed. However, AD-LBP descriptor cannot effectively provide a reliable and meaningful description of texture. Moreover, to sufficiently utilize "nonuniform" local patterns, Khellah et al.[25] proposed dominant neighborhood structure (DNS) and Guo et al.[26] developed discriminative features for texture description.

Guo et al.[27] designed a learning framework of image descriptor based on the Fisher separation criteria (FSC) to learn most reliable and robust dominant pattern types considering intra-class similarity and inter-class distance. Furthermore, Guo et al. developed a new FSC-based learning (FBL-LBP) descriptor. FBL-LBP differs from previous LBP approaches since FBL framework learns robust dominant types of each class instead of using fixed pattern types. In addition, this learning framework is easy to generalize for other purposes by introducing different histogram descriptors. Zhao et al.[28] presented the local binary count (LBC) method for texture classification. LBC extracts the local binary gray-scale difference information and totally abandons the local binary structural information. Furthermore, LBC demonstrated that the local gray-scale difference information plays a main role in the LBP for rotation invariant texture classification. Besides, Fathi et al.[29] proposed a noise tolerant extension of LBP operators to extract statistical and structural image features for efficient texture analysis.

The methods to color texture analysis can be roughly divided into two categories: methods that process color and texture information separately, and those that consider color and texture a joint phenomenon. Mäenpää et al.[30] argued that adding color information to texture measures indeed increases accuracy, while obtained with a three times longer feature vector. His study suggested that using color and texture in parallel is not the most powerful way of utilizing this complementary information. All joint color texture descriptors and all methods of combining color and texture on a higher level are outperformed by either color or gray-scale texture alone.

Mäenpää et al.[31] proposed an method based on separate processing of complementary color and pattern information, while this method needs to calculate nine LBP images. To solve above issue, Porebski et al.[32] presented a new method for color texture classification by use of Haralick features extracted from co-occurrence matrices computed from LBP images. Recently, Zhang et al.[33] proposed the local energy pattern (LEP) method for dynamic texture classification, similarly, Zhao et al.[34] exploited a novel approach to compute rotation-invariant features from histograms of local noninvariant patterns, which can effectively deal with rotation variations of dynamic textures (DTs).

In addition to the above improvements in LBP methods, some texture analysis methods are also motivated by LBP. For instance: Ojansivu et al.[35] exploited the local phase quantization (LPQ) method for texture classification; Lategahn et al.[36] introduced Gaussian mixture models (GMM) into joint probability density functions (JPDF) for texture classification; Chen et al.[37] developed weber local descriptor (WLD), and Liu et al.[38] proposed sorted random projections (SRP) method.

3 LBP methods in face analysis and recognition

LBP method not only shows superior performance in the texture analysis and classification of the application, but also gets the same good effect in face recognition application. Several kinds of influential LBP improvement methods in face recognition application are discussed and analyzed as follows.

3.1 Elongated LBP (ELBP)

Liao et al.[39] proposed the elongated LBP (ELBP) method for face recognition, and developed a new feature which is called average maximum distance gradient magnitude (AMDGM). AMDGM embeds the gray level difference information between the reference pixel and neighboring pixels in each ELBP pattern. There are three parameters related to the ELBP approach: the long axis of the ellipse, denoted by A=2; the short axis of the ellipse, denoted by B=3; the number of neighboring pixels, denoted by m. Fig. 5 shows examples of the ELBP patterns with different values of A, B, and m.

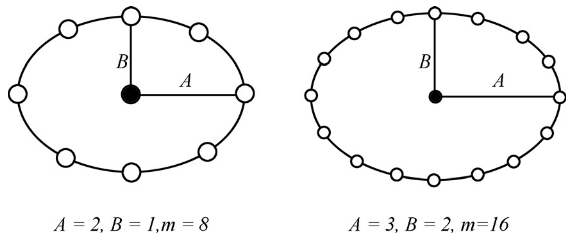

Fig. 5 Examples of ELBP with different values of A, B, and m

In fact, the ELBP features are more general than the conventional LBP, more precisely, the conventional LBP can be viewed as a special case of ELBP when setting the values of A and B equal to each other. The ELBP is able to capture anisotropic information from the facial images, which are important features as there are many important parts in the face such as eyes, mouth are all elongated structures. Therefore, it is expected that ELBP can have more discriminative power than the conventional LBP.

3.2 Improved local binary pattern (ILBP)

Jin et al.[40] presented a novel face detection approach using improved local binary patterns (ILBP) as facial representation. In most cases, the central point provides more information than its neighborhood. To get all the representations of LBP, ILBP considers the effect of the central pixel and gives it the largest weight. Fig. 6 shows the distribution of ILBP weight.

ILBP is defined as follows:

$$\begin{aligned} &LBP_{P,R} = \sum_{i=0}^{P-1} s(g_i - m)2^i + s(g_c - m)2^P, \\ &s(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases} \end{aligned} \tag{19}$$

where $m = \frac{1}{P+1}(\sum\limits_{i=0}^{P-1} g_i - g_c)$.

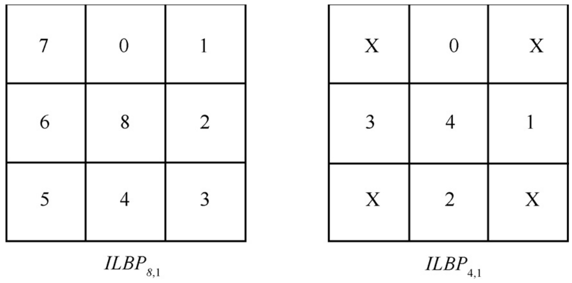

Fig. 6 Mapping weights for $ILBP_{8,1}$ and $ILBP_{4,1}$ ("X" indicates arbitrary pixel value)

The ILBP features are insensitive to the variation of illumination, there is no need to do image enhancement such as illumination equalization to remove the influence of light. But there is a need to improve the computing efficiency and performance by using other new classifiers and more ILBP features at different neighborhood.

3.3 Local line binary patterns (LLBP)

Petpon et al.[41] introduced a novel face representation method for face recognition, called local line binary pattern (LLBP), which summarizes the local spacial structure of an image by thresholding the local window with binary weight and introducing the decimal number as a texture presentation. Moreover it requires less computational cost. Coding way of LLBP is shown in Fig. 7.

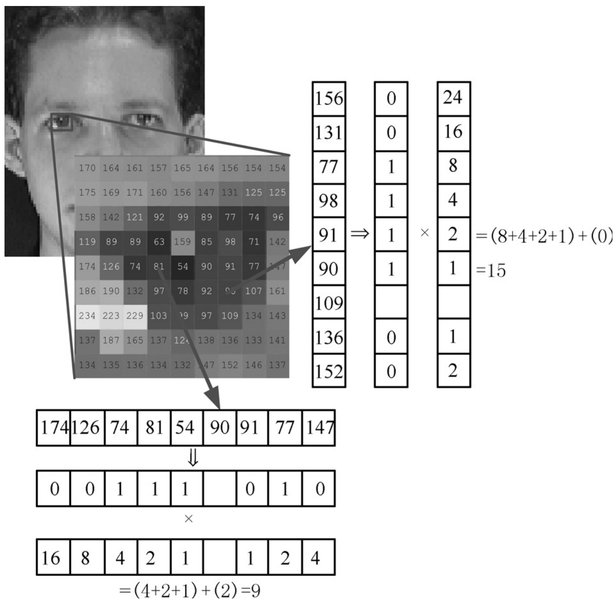

Fig. 7 LLBP operator with line length of 9 pixels

The basic idea of LLBP is to first obtain the line binary code along with horizontal and vertical direction seperately and then compute its magnitude, which characterizes the change in image intensity such as edges and corners. Consequently, LLBP is more discriminative than other methods even in extreme illumination condition. However, LLBP needs to increase the discriminative power in macrostructure of the image.

3.4 Local ternary patterns (LTP)

Tan et al.[42] introduced the local ternary patterns (LTP), which is less sensitive to noise in uniform regions. LTP extends LBP to 3-valued codes, in which gray-levels in a zone of width $\pm\ t$ around are quantized to zero, and the ones above this are quantized to $+1$ and ones below it to -1. Coding way of LTP is shown in Fig. 8.

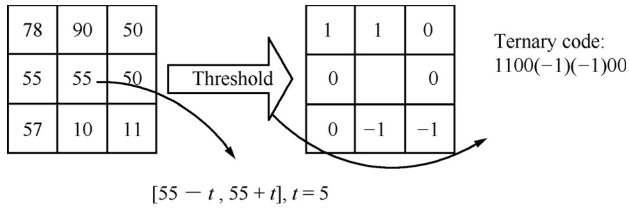

Fig. 8 Illustration of the basic LTP

The calculation of the three values is shown as follows:

$$s'(u, i_c, t) = \begin{cases} 1, & u \geq i_c + t \\ 0, & |u - i_c| < t \\ -1, & u \leq i_c - t \end{cases} \tag{20}$$

where t is a user-specified threshold, which is set as 5 in Fig. 8, hence its tolerance interval is [50, 60].

For simplicity, the experiments of LTP use a coding scheme that splits each ternary pattern into its positive and negative halves as illustrated in Fig. 9. Subsequently, LTP treats these components as two separate channels of LBP descriptors for which separate histograms and similarity metrics are computed, by combining the results only at the end of the computation.

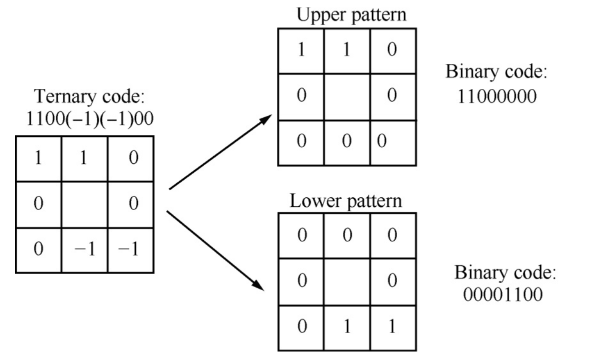

Fig. 9 Splitting an LTP code into positive and negative LBP codes

LTP has a stronger discrimination ability against the changes of noise and illumination than LBP in the uniform region. But the issues of image multiscale variation and partial occlusion are needed to solve.

3.5 Multi-scale block local binary patterns (MB-LBP)

Liao et al.[43] proposed a novel representation, called multiscale block local binary pattern (MB-LBP), and applied it to face recognition. In MB-LBP, the computation is done based on average values of block subregions, instead of individual pixels, its principle is shown in Fig. 10.

In each sub-region, average sum of image intensity is computed. These average sums are then thresholded by that of the center block. MB-LBP is then obtained.

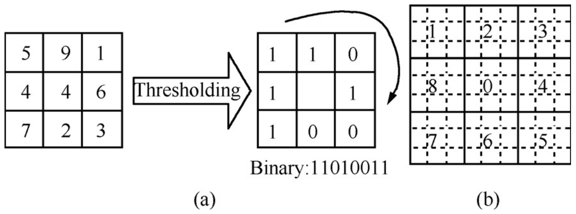

Fig. 10 The basic LBP((a)) and the 9×9 MB-LBP((b))

MB-LBP encodes not only microstructures but also macrostructures of image patterns, hence provides a more completed image representation than the basic LBP. The question of how to make the MB-LBP block size has better representation of the image information sill needs further study. In addition, Zhang et al.[44] also proposed a similar MB-LBP.

3.6 Three-Patch LBP (TP-LBP)

Wolf et al.[45] exploited the three-patch LBP (TPLBP) method, which is produced by comparing the values of three patches to produce a single bit value in the code assigned to each pixel. For each pixel in the image, TPLBP considers a $w \times w$ patch centered on the pixel and S additional patches distributed uniformly in a ring of radius r around it (Fig. 11). For α parameter, TPLBP takes pairs of patches (α-patches apart along the circle), and compares their values with those of the central patch. The value of a single bit is set according to which of the two patches is more similar to the central patch. The resulting code has S bits per pixel.

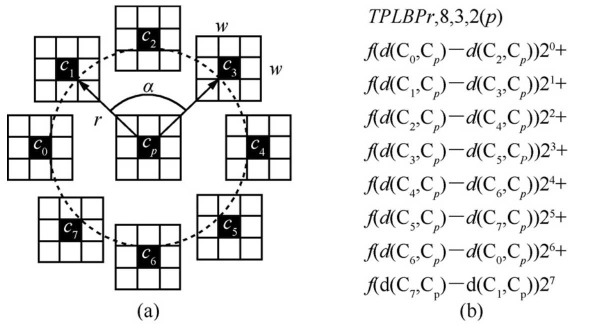

Fig. 11 The coding principle of TP-LBP with $S = 8$, $W = 3$, $\alpha = 2$ ((a)) and the computing method of TP-LBP code with $S = 8$, $W = 3$, $\alpha = 2$ ((b))

However, some of the experiments of TPLBP are partial due to the computational complexity of the similarity based method. Moreover, TP-LBP is unable to conduct experiments on more than 100 classes.

To compare the experimental results accuracy of above several methods, Table 2 respectively gives the classification accuracy on ORL database[46], Yale B database[47], FERET database[48], FRGC database[49], and LFW database [50]. We cannot comprehensively evaluate the performance of these methods, since only the experimental results of above methods are given in one or two of the databases. However, in the available data: the classification precision of LTP is the best in the same Yale B database; LLBP and MB-LBP obtained the same average recognition rate; in the same FRGC database, the classification accuracy of LTP is lower than that of MB-LBP. In addition, Huang et al.[51] reviewed the improved LBP methods for face recognition.

3.7 Other methods

Chan et al.[52] proposed a novel discriminative face representation derived by the linear discriminant analysis (LDA) of multispectral local binary pattern histograms for color face recognition. In this method, the color face image is first photometrically normalized and partitioned into several non-overlapping regions, and then multispectral local binary pattern histograms are extracted and concatenated into a regional feature. The feature is then projected into a LDA space to be used as a regional discriminative facial descriptor. Furthermore, Chan et al.[53] extended the method to multi-scale local binary pattern histograms for face recognition.

Zhang et al.[54] exploited a non-statistics based face representation method, namely local gabor binary pattern histogram sequence (LGBPHS), in which training procedure is unnecessary to construct the face model, and LGBPHS avoids the generalizability issue. This method modeled a face image as a "histogram sequence" by concatenating the histograms of all the local regions for the local Gabor magnitude binary pattern maps. Although this method achieved commendable result on FERET face database, the effective and efficient match of two LGBPHSes, especially for pose and occlusion variations are still needed to study. Tan et al.[55] combined two of the most successful local face representations, Gabor wavelets and LBP. And they argued that robust recognition requires several different kinds of appearance information, and suggested the use of heterogeneous feature sets. In addition, Shan et al.[56] developed a statistical extension for local gabor binary pattern (LGBP) similarity computation by introducing Fisher discriminant analysis (FDA) of the LGBP spatial histogram "features".

Maturana et al.[57] introduced and analyzed a generalization of LBP, decision tree local binary patterns (DT-LBP), which learns the most discriminative LBP-like features for each facial region in a supervised manner. In this method, the tree has S levels, where all the nodes at a generic level l compare the center pixel with a given neighbor. Lahdenoja et al.[58] proposed a method for reducing the length of the feature vectors in the LBP based face recognition, which defines a discrimination concept of the uniform local binary patterns called symmetry. Moreover, Zhang et al.[59] exploited a high-order local pattern descriptor, local derivative pattern (LDP), which is a general framework to encode directional pattern features based on local deriva-

Table 2 The average recognition rates of various methods on different databases ("–"indicates no data.) (%)

Method	ORL database	Yale B database	FERET database	FRGC database	LFW database	Note
ELBP[39]	97.0	–	86.7	–	–	
ILBP[40]	–	84.4	–	–	–	
LLBP[41]	–	89.7	–	–	–	
LTP[42]	–	98.7	–	86.3	–	
MB-LBP[43]	–	89.7	–	98.3	–	
TP-LBP[45]	–	–	–	–	76.5	

tive variations.

Shan et al.[60] developed the learn discriminative LBP-histogram (LBPH) bins for the task of facial expression recognition. This method adopted the Adaboost to learn the most discriminative sub-regions (in term of LBP histogram) from a large pool of sub-regions generated by shifting and scaling a sub-window over face images. Furthermore, An et al.[61] introduced a architecture of the future interactive TV and proposed a real-time face analysis system that can detect and recognize human faces and even their expressions, and therefore understand their internal emotional states.

Yan et al.[62] described the locally assembled binary (LAB) Haar feature for fast and accurate face detection. LAB modified the Haar features to keep only the ordinal relationship (named by binary Haar feature) rather than the difference between the accumulated intensities. Moreover, Roy et al.[63] also proposed a face detection system based on a new type of feature called the Haar local binary pattern (HLBP) feature which combines the advantages of both Haar and LBP.

Yang et al.[64] introduced the widely used Hamming distance to decrease the error rate caused by some noise disturbances (assuming that the illumination, pose or expression changes of a face image are some kinds of "noise"). Fu et al.[65] proposed the centralized binary pattern (CBP) operator, which reduces significantly the histograms′ dimensionality by comparing pairs of neighbors in the operator. CBP considers the center pixel points effect and gives it the largest weight, thus improving discrimination. Furthermore, CBP also decreases the white noise′s influence on face images. In addition, Zhang et al.[66] presented a method for face recognition which used boosted statistical local feature based classifiers.

4 LBP methods in other detection applications

Not only does LBP method get remarkable achievements in the field of texture analysis and classification, face analysis and recognition, but also it is applied in pedestrian detection, car detection, image matching and facial expression recognition etc. The mentioned methods are discussed and analyzed as follows.

4.1 Applications in pedestrian detection

Mu et al.[67] applied LBP in pedestrian detection and proposed two descriptors: semantic-LBP (S-LBP) and Fourier-LBP (F-LBP). Since the feature vector of LBP requires huge storage and cannot represent the semantically similar features, the S-LBP descriptor is proposed to deal with these issues. The definition of S-LBP is like this: several continued "1" bits form an arch on the sampling circle, which can be compactly represented with its principle direction and arch length. 2D histogram descriptor for any image region can be obtained by collecting information from the features. Finally S-LBP concatenates each column of the 2D histogram to get a 1D vector. Fig. 12 shows the computing principle of S-LBP.

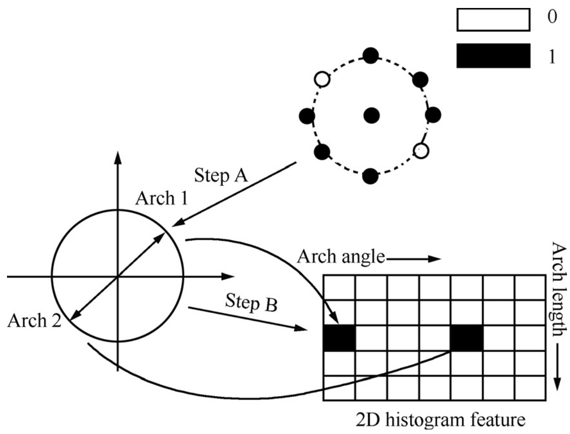

Fig. 12 The computing principle of S-LBP

F-LBP descriptor is a "soft" LBP, i.e., skipping the binarization step when calculating LBP. It avoids the potential errors caused by improper local thresholding and thus controllable compression is possible. F-LBP uses $s(k)$ $(k = 0, \cdots, P-1)$ to denote raw feature vector, where $s(k)$ is real-valued color distance between the kth samples and central pixel. F-LBP transforms the feature vector into frequency domain. Coefficients for low frequencies are more useful since they capture salient local structures around current pixel, and lossy compression can be obtained via dropping some highest frequency coefficients. One-dimensional DFT used in feature vector transformation is like this:

$$a(u) = \frac{1}{P}\sum_{k=0}^{P-1} s(k)\mathrm{e}^{\frac{-j2\pi uk}{P}} \tag{21}$$

Mu et al. used these descriptors to conduct a series of experiments on the INRIA pedestrian dataset[68], and got excellent results. However, the method lost partial contour information. Wang et al.[69] solved this problem and got a better detection result by combining LBP and HOG.

4.2 Applications in car detection

Trefny et al.[70] proposed two descriptors: transition LBP (tLBP) and direction LBP (dLBP), and applied the two descriptors in car detection. The LBP encoding rule thresholds the neighbor gray values by its center pixel value. This gives rough knowledge of pixel with respect to the center one, while relations between pixels with the same binary value are lost. However, binary value of tLBP is composed of neighbor pixel comparisons in clockwise direction for all pixels except the central. Thus this rule encodes relation between neighbor pixels. More precisely let g_p correspond to gray value pth neighbor of center pixel, then

$$tLBP_{P,\mathrm{R}} = s(\mathrm{g}_0 - \mathrm{g}_{P-1}) + \sum_{p=1}^{P-1} s(\mathrm{g}_p - \mathrm{g}_{p-1})2^p \tag{22}$$

The dLBP descriptor provides better information of local pattern in sense of direction functions. There are four base directions through the center pixel in LBP, see Fig. 13. The dLBP encodes intensity variation along these directions into two bits: the first bit encodes, whether the center pixel is an extrema and the second bit encodes, whether the difference of border pixels due to the center one grows or declines. Let $P = 2P'$, so $\mathrm{dLBP}_{P,R}$ can be written as follows:

$$\begin{aligned} dLBP_{P,\mathrm{R}} = &\sum_{p'=1}^{P'-1}(s((g_{p'} - g_c)(\mathrm{g}_{p'+\mathrm{P}'} - \mathrm{g}_c))2^{2p'} + \\ &s(|g_{p'} - g_c| - |g_{p'+P'} - g_c|)2^{2p'+1}) \end{aligned} \tag{23}$$

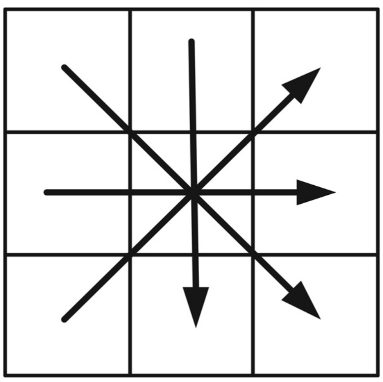

Fig. 13 Four basic directions of coding LBP

Trefny et al.[70] used these two descriptors to conduct experiments on car dataset of UIUC[71], and got high detection precision. But it doesn't work well when the object is in different scales or in partial occlusion.

4.3 Applications in image matching

Heikkilä et al.[72] described the Center Symmetric LBP (CS-LBP) descriptor, which is used in normalized interest region. The problems in LBP method i.e. having a rather long histogram and no robustness in flat image regions are solved by CS-LBP. CS-LBP encodes the patterns by two pixels center-symmetric, and produces only 16 different binary patterns while LBP produces 256. It can be formulated as follows:

$$\begin{aligned} &CS - LBP_{R,P,T} = \sum_{i=0}^{P/2-1} s(g_i - g_{i+P/2})2^i, \\ &s(x) = \begin{cases} 1, & x > T \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{24}$$

Heikkilä et al[72]. used many images with six different kinds of situations: viewpoint change, scale change, image rotation, image blur, illumination change and JPEG compression. By combining the SIFT descriptor, using a SIFT-like grid and LBP texture operator, CS-LBP obtained higher matching accuracy rate.

4.4 Applications in facial expression recognition

Zhao et al.[73] proposed volume LBP (VLBP) descriptor and LBP Three Orthogonal Planes (LBP-TOP) descriptor for facial expression recognition. VLBP describes dynamic texture in a local neighborhood, and extends LBP to DT (dynamic texture) analysis. The descriptor gets local binary pattern of three images with time interval L ($t_c - L$, t_c, $t_c + L$) respectively. Each $VLBP_{L,P,R}$ descriptor has five parts at five different moments: local neighborhood center pixel pattern at time $t_c - L$ and $t_c + L$, binary pattern composed of local neighborhood P-pixels at time $t_c - L$, t_c and $t_c + L$.

In the proposed VLBP, the parameter P determines the number of features. A large P produces a long histogram, while a small P makes the feature vector shorter and means more loss of information. To address the problem, the authors simplified the descriptor by concatenating local binary pattern on three orthogonal planes: XY, XT, and YT, considering only the co-occurrence statistics in these three directions. The LBP code is extracted from the three orthogonal planes respectively. And DT is encoded by the XY-LBP, XT-LBP and YT-LBP while the appearance and motion in three directions of DT are considered. The calculation procedures of incorporation spatial domain information (XY-LBP) and two spatial temporal co-occurrence statistics (XT-LBP and YT-LBP) are shown in Fig. 14.

Zhao et al.[73] conducted a series of experiments on the facial expression dataset of Cohn-Kanade[74], and achieved an accuracy rate of 94.38 % when only using LBP-TOP descriptor, while the accuracy rate rose up to 95.19 % by combining the two descriptors: LBP-TOP and VLBP.

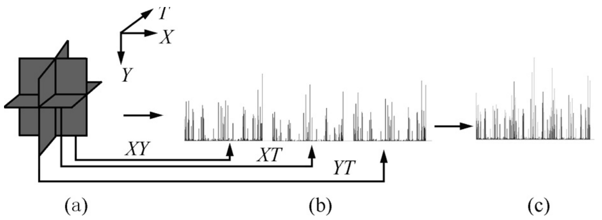

Fig. 14 Three orthogonal planes ((a)), LBP histogram from each plane ((b)), concatenated feature histogram ((c))

4.5 Applications in other fields

Many researchers applied LBP in other fields except for pedestrian detection, car detection, image matching and facial expression recognition. Heikkilä et al.[75−76] applied LBP in background extraction and background modeling. They utilized the original LBP to solve background modeling problem with object partial occlusion. And the method is more efficient than that in [77], when used in foreground extraction. Based on the research of Heikkilä et al., Takala et al.[78], Yao et al.[79], and Liao et al.[80] applied LBP in multi-object extracting, multi-hierarchy background extracting and 3D background modeling respectively, and they got satisfactory results. Moreover, LBP was used into gesture recognition and gait recognition by Kellokumpu et al.[81−84], and a high recognition rate was obtained. Costa et al.[85] applied LBP in music genre classification.

5 The issues and research direction

Despite the fruitful and significant progress made in the current studies of local binary pattern method, more innovative research in the perspectives of theory and algorithm is necessary with regard to the problems concerning natural image texture analysis and dynamic target detection and recognition, which are becoming increasingly complex in the practical engineering. The research will better indicate the target and texture features and carry forward wider application of LBP method in practical engineering while optimizing theoretical analyses. The remaining significant problems include:

1) Lacking of an LBP texture analysis method that is more robust to illumination change, affine transformation and noise interference. Since the basic processing of LBP method is the operation on threshold values, it is sensitive to noise and illumination changes. Though researchers have put forwarded various solutions, e.g., He et al.′s Bayesian LBP, Ahonen et al.[20]′s soft histograms, and Zhou et al.[23]′s extended LBP have ameliorated the method to avoid such problems, the solutions can only improve the robustness of LBP to the interferences rather than radically eliminating the instability brought about by the operation on threshold values. Therefore it is necessary to study the factors of the instability and solve the problem in order to realize a more robust LBP texture analysis coping with the illumination change, affine transformation and noise interference.

2) A texture analysis taking full advantage of the non-uniform mode of LBP is needed. Ojala et al.[4] put forward a unified model with the purpose of reducing the variety of local binary patterns and putting all the non-uniform modes into one category. However, this process left out much texture information in non-uniform modes, which becomes especially evident when large neighborhood is applied. Though Zhou et al[23]. proposed to divide non-uniform modes into two subsets, i.e., the ones indicating structural information and ones indicating probability of occurrence, and obtained desirable results using Brodatz texture database[12], it was not so effective in smaller neighborhood. Therefore, a further study on how to make the best of the non-uniform mode to better serve texture analysis is necessary.

3) Deficiency in LBP texture analysis methods applied on complex natural images. The current methods of LBP texture analysis are applied in experiments based on Brodatz database[13] and Outex database, which are not very complex, while ameliorated texture analysis methods that are applied in more challenging CUReT database[8] and KTHTIPS2b database[86−87] are still rare. Therefore further study on texture analysis methods of more complex natural images is necessary.

4) An in-depth study on LBP face analysis methods that are more robust to the changes of gesture and illumination is necessary. Much practice has shown that face recognition of computer is confronted with two challenges: changes of gesture and illumination. The inevitability of the aging of face, partial occlusion, disparities of imaging devices, make-up and ornaments under non-controllable and non-cooperative circumstances (e.g., video monitoring), and the frequency of concurrence of the factors mentioned above all add to difficulty of face recognition. Despite the various LBP improvements brought forward by researchers, e.g., Jin et al.[40]′s improved LBP, Tan et al.[42]′s local ternary patterns, Liao et al.[43]′s multi-scale block LBP, currently there is no comprehensive solution to the influences of unstable factors. Consequently, an intensive study on the resolution of the affecting factors is necessary to make LBP face analysis more robust to the changes of gesture and illumination.

5) Lack of an intensive study on LBP facial expression analysis of color images and physiological classification method. Currently, LBP face analysis mainly focuses on face detection and localization as well as classification and identification, while study on facial expression analysis and physiological classification is still in the primary stage. Consequently, more and more researchers have turned their attention to the analysis of facial expression. Shan et al.[60] detected facial expression applying histogram with LBP features; An et al.[61] designed a face recognizing system using facial expression. In addition, the existing image data of current study mainly focuses on gray image, while other color channel information of color image is still in need of further study. Therefore an intensive study on LBP facial expression analysis of color images and physiological clas-

sification is worthy of attention.

6) The need of extension of LBP application fusing other features. Currently multi-feature fusing method is the hot spot of the study of feature extraction. Therefore a wider application of LBP method needs further study on the fusion of LBP and other features.

6 Conclusion

LBP method is not only relatively simple and of low computation complexity, but also has a rotational invariance, gray scale invariance and other significant advantages. Therefore, LBP has obtained fruitful results and is widely used in image matching, pedestrian and car target detection and tracking, as well as biological and medical image analysis. The principle of LBP method is briefly discussed; the texture analysis and classification, face analysis and recognition, and other detection applications of the LBP method are combed and commented in detail respectively; and the remaining significant issues of the LBP method are analyzed and the future directions are pointed out.

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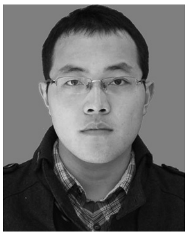

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