Local Binary Patterns and Its Application to Facial Image Analysis: A Survey

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***Abstract*—Local binary pattern (LBP) is a nonparametric descriptor, which efficiently summarizes the local structures of images. In recent years, it has aroused increasing interest in many areas of image processing and computer vision and has shown its effectiveness in a number of applications, in particular for facial image analysis, including tasks as diverse as face detection, face recognition, facial expression analysis, and demographic classification. This paper presents a comprehensive survey of LBP methodology, including several more recent variations. As a typical application of the LBP approach, LBP-based facial image analysis is extensively reviewed, while its successful extensions, which deal with various tasks of facial image analysis, are also highlighted.**

***Index Terms*—Face detection, face recognition, facial expression analysis, local binary patterns (LBPs), local features.**

I. Introduction

During the past few years, local binary patterns (LBPs) [1] have aroused increasing interest in image processing and computer vision. As a nonparametric method, LBP summarizes local structures of images efficiently by comparing each pixel with its neighboring pixels. The most important properties of LBP are its tolerance regarding monotonic illumination changes and its computational simplicity. LBP was originally proposed for texture analysis [2], and has proved a simple yet powerful approach to describe local structures. It has been extensively exploited in many applications, for instance, face image analysis [3], [4], image and video retrieval [5], [6], environment modeling [7], [8], visual inspection [9], [10], motion analysis [11], [12], biomedical and aerial image analysis [13], [14], and remote sensing [15] (see a comprehensive bibliography of LBP methodology online [16]).

LBP-based facial image analysis has been one of the most popular and successful applications in recent years. Facial image analysis is an active research topic in computer vision, with a wide range of important applications, e.g., human–computer interaction, biometric identification, surveillance and security, and computer animation. LBP has been exploited for facial representation in different tasks, which include face detection [4], [17]–[19], face recognition [20]–[26], facial expression analysis [27]–[31], demographic (gender, race, age, etc.) classification [32], [33], and other related applications [34], [35]. The development of LBP methodology can be well illustrated in facial image analysis, and most of its recent variations are proposed in this area.

Some brief surveys on image analysis [36] or face analysis [37]–[39], which use LBP, were given, but all these studies discussed limited papers of the literature, and many new related methods have appeared in more recent years. In this paper, we present a comprehensive survey of the LBP methodology, including its recent variations and LBP-based feature selection, as well as the application to facial image analysis. To the best of our knowledge, this paper is the first survey that extensively reviews LBP methodology and its application to facial image analysis, with more than 100 related reviewed literatures.

The remainder of this paper is organized as follows. The LBP methodology is introduced in Section II. Section III presents the recent variations of LBP. LBP-based feature-selection methods are discussed in Section IV. Section V describes different facets of its applications on facial image analysis. Finally, Section VI concludes the paper.

II. Local Binary Patterns

The original LBP operator labels the pixels of an image with decimal numbers, which are called *LBPs* or *LBP codes* that encode the local structure around each pixel. It proceeds thus, as illustrated in Fig. 1: Each pixel is compared with its eight neighbors in a 3×3 neighborhood by subtracting the center pixel value; the resulting strictly negative values are encoded with 0, and the others with 1. For each given pixel, a binary number is obtained by concatenating all these binary values in a clockwise direction, which starts from the one of its top-left neighbor. The corresponding decimal value of the generated binary number is then used for labeling the given pixel. The derived binary numbers are referred to be the LBPs or LBP codes.

One limitation of the basic LBP operator is that its small 3×3 neighborhood cannot capture dominant features with large-scale structures. To deal with the texture at different scales, the operator was later generalized to use neighborhoods of different sizes [1]. 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, and the sampling points that do not fall

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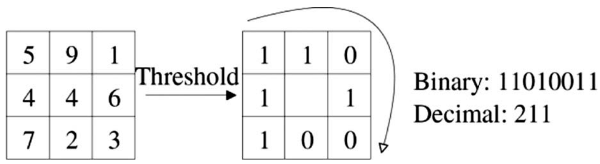

Fig. 1. Example of the basic LBP operator [3].

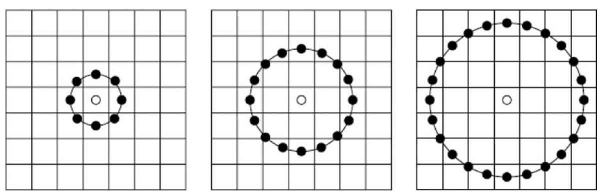

Fig. 2. Examples of the ELBP operator [20]. The circular (8, 1), (16, 2), and (24, 3) neighborhoods.

within the pixels are interpolated using bilinear interpolation, thus allowing for any radius and any number of sampling points in the neighborhood. Fig. 2 shows some examples of the extended LBP (ELBP) operator, where the notation (*P, R*) denotes a neighborhood of *P* sampling points on a circle of radius of *R*.

Formally, given a pixel at (x_c, y_c), the resulting LBP can be expressed in decimal form as follows:

$$\mathrm{LBP}_{P,\,R}(x_c, y_c) = \sum_{P=0}^{P-1} s(i_P - i_c) 2^P \tag{1}$$

where i_c and i_P are, respectively, gray-level values of the central pixel and *P* surrounding pixels in the circle neighborhood with a radius *R*, and function *s*(*x*) is defined as

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0. \end{cases} \tag{2}$$

From the aforementioned definition, the basic LBP operator is invariant to monotonic gray-scale transformations, which preserve pixel intensity order in the local neighborhoods. The histogram of LBP labels calculated over a region can be exploited as a texture descriptor.

The operator $\mathrm{LBP}_{(P,R)}$ produces 2^p different output values, corresponding to 2^p different binary patterns formed by *P* pixels in the neighborhood. If the image is rotated, these surrounding pixels in each neighborhood will move correspondingly along the perimeter of the circle, thus resulting in a different LBP value, except for patterns with only 1 and 0 s. In order to remove rotation effect, a rotation-invariant LBP is proposed in [1]

$$\mathrm{LBP}^{ri}_{P,\,R} = \min\{\mathrm{ROR}(\mathrm{LBP}_{P,\,R}, i)|, \quad i = 0,\ 1,\ \ldots,\ P-1\} \tag{3}$$

where ROR(*x, i*) performs a circular bitwise right shift, on the *P*-bit number *x*, *i* times. The $\mathrm{LBP}^{ri}_{(P,R)}$ operator quantifies occurrence statistics of individual rotation-invariant patterns, which correspond to certain microfeatures in the image; hence, the patterns can be considered to be a feature detector [1]. However, in [40], it was shown that such a rotation-invariant LBP operator does not necessarily provide discriminative information, since the occurrence frequencies of the individual patterns that are incorporated in $\mathrm{LBP}^{ri}_{(P,R)}$ vary greatly and the crude quantization of the angular spaces at 45° intervals.

It has been shown that certain patterns contain more information than others [1]. It is possible to use only a subset of 2^p binary patterns to describe the texture of images. Ojala *et al*. named these patterns *uniform patterns*, which are denoted as $\mathrm{LBP}^{U2}_{(P,R)}$. An LBP is called uniform, if it contains at most two bitwise transitions from 0 to 1 or *vice versa* when the corresponding bit string is considered circular. For instance, 00000000 (0 transitions) and 01110000 (2 transitions) are both uniform, whereas 11001001 (4 transitions) and 01010011 (6 transitions) are not. It is observed that the uniform patterns account for around 90% of all the patterns in a (8, 1) neighborhood, and around 70% in a (16, 2) neighborhood in texture images [1]. A similar experiment was conducted on the FERET database, and it was found that 90.6% of the patterns in a (8, 1) neighborhood, and 85.2% in a (8, 2) neighborhood are uniform [20]. More recently, Shan and Gritti [41] verified the validity of uniform patterns to represent faces from the viewpoint of machine learning. Specifically, they applied AdaBoost to select the discriminative patterns for facial expression recognition, and their experiments demonstrated that, by using $\mathrm{LBP}_{(8,2)}$ operator, 91.1% of these selected patterns are uniform. Accumulating the nonuniform patterns into a single bin yields an LBP operator with less than 2^p labels. For example, the number of labels with the neighborhood of 8 pixels is 256 for the standard LBP, but only 59 for LBP^{U2}.

It should be noted that, when the original LBP operator was proposed, Zabih and Woodfill introduced a census transform (CT) method [42], which is very similar to LBP. In addition, CT maps the local neighborhood, which surrounds a pixel onto a binary string, and the only difference between LBP and CT is the opposite order of bit string. Later, CT and its variations were exploited for facial image analysis [43]–[45].

The C/C++ and MATLAB implementations of the LBP operator can be found online [46].

III. Recent Variations of Local Binary Pattern

LBP methodology has been developed recently with large number of variations for improved performance in different applications. These variations focus on different aspects of the original LBP operator: 1) improvement of its discriminative capability; 2) enhancement of its robustness; 3) selection of its neighborhood; 4) extension to 3-D data; and 5) combination with other approaches. In this section, we review recent variations of LBP (see Table I for the overview).

A. Enhancing the Discriminative Capability

The LBP operator defines a certain number of patterns to describe the local structures. To enhance their discriminative capability, more patterns or information could be encoded. Jin *et al.* [17] modified the LBP operator to describe more local structure information under certain circumstances. Specifically, they proposed an improved LBP (ILBP), which compares all the pixels (including the central pixel) with the mean intensity of all the pixels in the patch (as shown in Fig. 3). For instance, the $\mathrm{LBP}_{(8,1)}$ operator produces only 256 (2^8) patterns in a 3 ×

TABLE I
LIST OF RECENT LBP VARIATIONS

Subsection	Variations	Properties	Year & Reference
A: Enhancing the discriminative ability	Improved LBP (Mean LBP)	Consider the effects of central pixels; present complete structure patterns.	2004 [17], 2005 [48] 2008 [49]
	Hamming LBP	Incorporate non-uniform patterns into uniform patterns	2007 [50]
	Extended LBP	Discriminate the same local binary patterns; cause high dimensionality.	2007 [51, 52]
	Completed LBP	Include both the sign and the magnitude information of the given local region	2010 [53]
B: Improving the robustness	Local Ternary Patterns	Bring in new threshold; no longer strictly invariant to gray-level transformation.	2007 [22]
	Soft LBP	Not invariant to monotonic grayscale changes; cause high computational complexity.	2007 [54]
C: Choosing the neighborhood	Elongated LBP	Extract the anisotropic information and lose anisotropic information; not invariant to rotation.	2007 [23]
	Multi-Block LBP	Capture micro- and macro- structure information	2007 [18, 55]
	Three/Four Patch LBP	Encode patch type of texture information	2008 [57]
D: Extending to 3D	3D LBP	Extend LBP to 3D volume data	2007 [58], 2008 [59]
	Volume LBP (LBP-TOP)	Describe dynamic texture; cause high dimensionality.	2007 [30, 60]
E: Combining with other features	LBP and Gabor Wavelet	Combine advantages of Gabor and LBP; increase time cost and cause high dimensionality.	2005 [67, 70], 2006 [68] 2007 [64, 65], 2008 [66, 71]
	LBP and SIFT	Bring in the advantages of SIFT; reduce feature vector length	2006 [72], 2009 [73] 2010 [76]
	LBP Histogram Fourier	Obtain rotation invariance globally for the whole region	2009 [77]

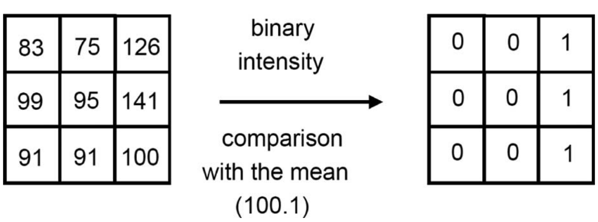

Fig. 3. Example of the ILBP operator [37].

3 neighborhood, while ILBP has 511 patterns ($2^9 - 1$, as all zeros and all ones are the same). Later, ILBP was extended to use the neighborhoods of any size instead of the original 3×3 patch [47]. Almost at the same time, a similar scheme was used to extend CT to modified CT [43], namely, modified LBP (MLBP) in [48]. A mean LBP [49] is presented, which is similar to ILBP, but without considering the central pixels.

Yang and Wang [50] proposed Hamming LBP to improve the discriminative ability of the original LBP. They reclassified nonuniform patterns based on Hamming distance, instead of collecting them into a single bin as LBP^{u2} does. In the Hamming LBP, these nonuniform patterns are incorporated into existing uniform patterns by minimizing the Hamming distance between them; for example, the nonuniform pattern $(10001110)_2$ is converted into the uniform one $(10001111)_2$, since their Hamming distance is one. When several uniform patterns have the same Hamming distance with a nonuniform pattern, the one with the minimum Euclidian distance will be selected.

The ELBP [51], [52] is another approach to improve the discriminative capability of LBP. The ELBP operator not only performs binary comparison between the central pixel and its neighbors, but also encodes their exact gray-value differences (*GDs*) using some additional binary units. Specifically, the ELBP feature consists of several LBP codes at multiple layers, which encode the *GD* between the central pixel and its neighboring pixels. As shown in Fig. 4, the first layer of ELBP is actually the original LBP code that encodes the sign of *GD*. The following layers of ELBP then encode the absolute value of *GD*. Basically, each absolute *GD* value is first encoded in its binary representation, and then all the binary values at a given layer result in an additional LBP. For example, in Fig. 4, the first layer is the original LBP code that encodes the sign of *GD*, thus yielding a decimal number of 211 from its binary form $(11010011)_2$. The absolute values of *GD*, i.e., 1, 5, 3, 2, 1, 2, 3, and 0, are first encoded in their binary numbers: $(001)_2, (101)_2, (011)_2, (010)_2, \ldots$, etc. Using a same weight scheme of LBP on all the binary bits, its ELBP code of the corresponding layer can be generated, e.g., L_2 is composed of $(01000000)_2$, and its decimal value is 64; L_3 is composed of $(00110110)_2$, and its decimal value is 54; finally, L_4 is composed of $(11101010)_2$, and its decimal value is 234. As a result, when describing similar local textures, although the first layer LBP is not discriminative enough, the information encoded in the other additional layers can be utilized to distinguish them. Its downside is that ELBP increases feature dimensionality to a large extent.

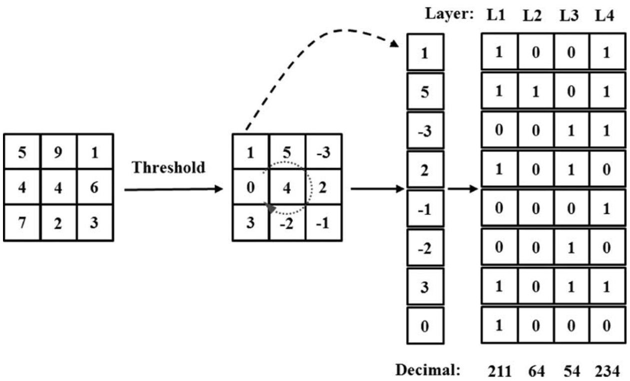

Fig. 4. Example of the ELBP operator.

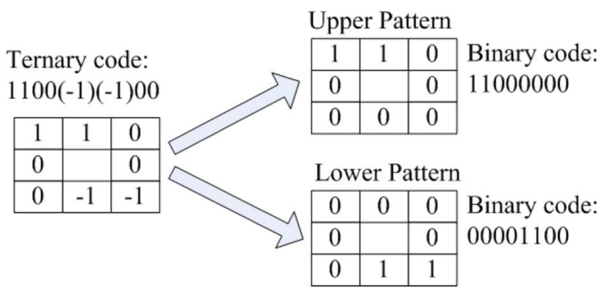

Fig. 5. Example of the LTP operator [22].

More recently, Guo *et al*. proposed a complete LBP (CLBP) [53], which, in our opinion, is quite similar with ELBP. In addition, CLBP includes both the sign and the GDs between a given central pixel and its neighbors in order to improve the discriminative power of the original LBP operator. Unlike the binary bit coding strategy used by ELBP, CLBP compares the absolute value of GD with the given central pixel again to generate an LBP-liked code.

B. Improving the Robustness

LBP is sensitive to noise, since the operator thresholds exactly at the value of central pixel. To address this problem, Tan and Triggs [22] extended the original LBP to a version with 3-value codes, which is called local ternary patterns (LTPs). In LTP, indicator $s(x)$ in (1) is replaced by

$$s\left(i_n,\ i_c,\ t\right) = \begin{cases} 1, & i_n \geq i_c + t \\ 0, & |i_n - i_c| < t \\ -1, & i_n \leq i_c - t \end{cases} \tag{4}$$

where t is a user-specified threshold. The LTP codes are more resistant to noise, but no longer strictly invariant to gray-level transformations. A coding scheme is used to split each ternary pattern into two parts: the positive one and the negative one, as illustrated in Fig. 5. One problem of LTP is to set threshold t, which is not simple.

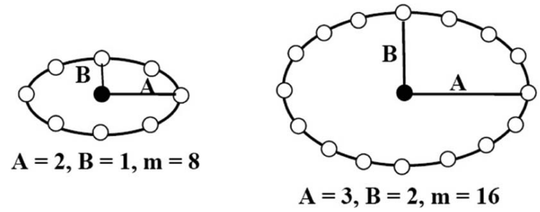

Fig. 6. Two examples of the elongated LBP operator [23].

The soft LBP (SLBP) was introduced in [54], which employs two fuzzy membership functions instead of (2)

$$s_{1,d}(x) = \begin{cases} 0, & x < -d \\ 0.5 + 0.5\dfrac{x}{d}, & -d \leq x \leq d \\ 1, & x > d \end{cases} \tag{5}$$

$$s_{0,d}(x) = 1 - s_{1,d}(x). \tag{6}$$

Parameter d controls the amount of fuzzification, which is performed by the fuzzy function. When the local neighborhood consists of P sampling points, the histogram with a uniform pattern operator has bins numbered 0, 1, …, $2^p - 1$. The contribution of a single pixel $(x_c,\ y_c)$ to bin h of the histogram is

$$\mathrm{SLBP}(x_c, y_c, h) = \prod_{p=0}^{P-1} [b_p(h) \cdot s_{1,d}(i_p - i_c) + (1 - b_p(h)) \cdot s_{0,d}(i_p - i_c)] \tag{7}$$

where $b_p(h) \in \{0{,}1\}$ denotes the numerical value of the pth bit of binary representation of h.

With SLBP, one pixel contributes to more than one bin, but the sum of the contributions of the pixel to all bins is always 1. SLBP enhances the robustness in the sense that a small change in the input image causes only a small change in output. However, it loses the invariance to monotonic variations, as well as increases the computation complexity. As with LTP, a proper value of d should be set.

C. Choosing the Neighborhood

The choice of an appropriate neighborhood for LBP-based techniques has a significant impact on the final performance. It involves the number of sampling points, the distribution of the sampling points, the shape of the neighborhood, and the size of the neighborhood.

Neighboring pixels in the original LBP are defined on a circle. Liao and Chung [23] argued that the main reason to define the neighborhood in such an isotropic manner is to obtain rotation invariance for texture description. However, this is not suitable for all applications; on the contrary, the anisotropic information could also be an important feature. As a result, they proposed elongated LBP with neighboring pixels lying on an ellipse. Fig. 6 shows two examples of the elongated LBP, where A and B denote the long axis and short axis, respectively, and m is the number of neighboring pixels. Followed by the original LBP, bilinear interpolation technique is adopted for neighboring pixels that do not fall exactly at the pixels. The elongated LBP operator

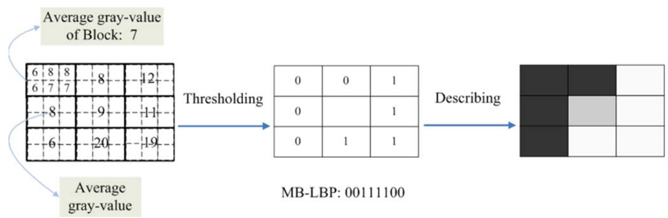

Fig. 7. Example of the MB-LBP operator [18].

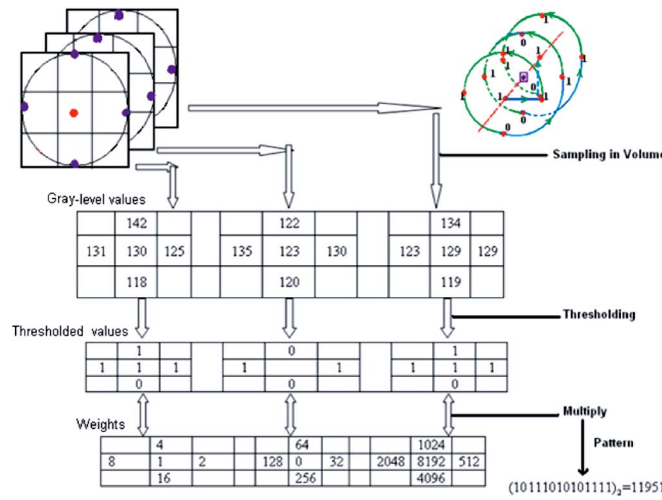

Fig. 8. Procedure of $\mathrm{VLBP}_{1,4,1}$ [60].

could be rotated around the central pixel, with a specific angle to characterize elongated local structures in different orientations, to achieve multiorientation analysis.

In order to capture not only the microstructures but also the macrostructures, Li *et al.* [18], [55] proposed a multiblock LBP (MB-LBP), which, instead of comparing pixels, compares average intensities of neighboring subregions. The original LBP can be regarded as a special case of the MB-LBP. Fig. 7 shows an example of MB-LBP, where each subregion consists of six pixels. The subregion can either be a rectangle or a square. The average intensities over the blocks can be computed efficiently by using summed-area table [56] or integral image. A similar scheme is introduced in [57]: Three-patch LBP (TP-LBP) and four-patch LBP (FP-LBP) are proposed to compare distances between the whole blocks (patches) concerned, instead of single pixel [1] or average intensity in [55], and any distance function can be used (e.g., L2-norm of their gray-level differences).

D. Extending to 3-D Local Binary Pattern

Several researchers have been trying to extend the LBP from 2-D plane to 3-D volume [30], [58]–[60]; however, it is not as straightforward as it appears at first glance. There are two difficulties: First, equidistant sampling on a sphere is a difficult job, and second, it is also difficult to set an order to those sampling points, which is important to achieve rotation invariance.

To endow the LBP with the ability to capture dynamic texture information, Zhao and Pietikäinen [30], [60] extended the LBP neighborhood from 2-D plane to 3-D space. The operator is named as volume LBP (VLBP or 3-D-LBP). VLBP combines motion and appearance information, and can thus be used to analyze image sequences or videos. It should be noted that this approach makes use of dynamic texture analysis of 2-D time series instead of full 3-D volumetric data. The VLBP features are not only insensitive to translation and rotation (toward rotations around the z axis), but also robust to monotonic gray-scale changes. Compared with $\mathrm{LBP}_{(P,R)}$, $\mathrm{VLBP}_{(L,P,R)}$ takes time domain into account, and the parameter L denotes the length of the time interval. From a small local neighborhood in volume, comparing neighboring pixels with the central pixel, a number of binary units are obtained, and the weights for these units are given as a spiral line (see Fig. 8). In order to make VLBP computationally simple and easy to extend, only co-occurrences on three separate planes are considered. The textures are modeled with the concatenated LBP histograms extracted from three orthogonal planes X–Y, X–T, and Y–T, and, thus, this simpler version of VLBP is named LBP-TOP. The traditional circular sampling is replaced by an ellipse so that different radius parameters can be set in the space and time domain.

Fehr [58] exploited the spherical harmonic transform to produce an orthogonal basis on the two-sphere, and then, compute the LBP features in the frequency domain. This method overcomes both the aforementioned problems. Paulhac *et al*. proposed another solution to apply LBP to 3-D [59]. They used a number of circles to represent the sphere, adding the parameter S, thus the operator denotes $LBP_{(S,PR)}$ (see Fig. 9), and they also defined the uniform rule as in 2-D. This method causes the problem that different textures could have the same LBP description.

E. Combining With Other Features

As a method to describe local features, LBP can be combined with other approaches. For example, a set of approaches was proposed to combine Gabor wavelets [61]–[63] and LBP features by using different methods. It was concluded in [64]–[66] that Gabor-wavelet- and LBP-based features are mutually complementary because LBP captures the local appearance detail, whereas Gabor wavelets extract shape information over a broader range of scales. A simple fusion strategy is to first extract Gabor and LBP features in the parallel way, and then, fuse two kinds of features on feature level, matching score level, or decision level [65], [66].

Another way of combination is the serial strategy, which consists in first applying Gabor filters and, then, LBP to the raw image [24], [67]. The multiple Gabor feature maps (GFMs) are computed by convolving input images with multiscale and multiorientation Gabor filters. Each GFM is divided into small nonoverlapped regions, from which LBP histograms are extracted and, finally, concatenated into a single-feature histogram. Multiresolution histograms of local variation patterns (MHLVPs) [24] as well as local Gabor binary pattern histogram (LGBPH) [67]–[69] have been proposed on the basis of such a procedure. Recently, He *et al.* [70] proposed a similar serial method by using both wavelets and LBP, which first uses wavelets to decompose raw images into four frequency images,

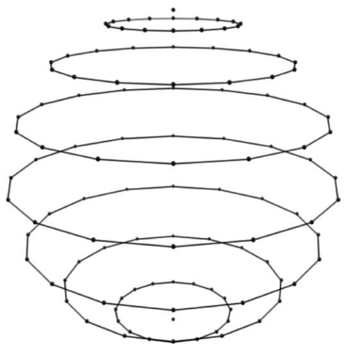

Fig. 9. Representation of a 3-D LBP ($S = 9$, $P = 16$, and $R = 2$) [59].

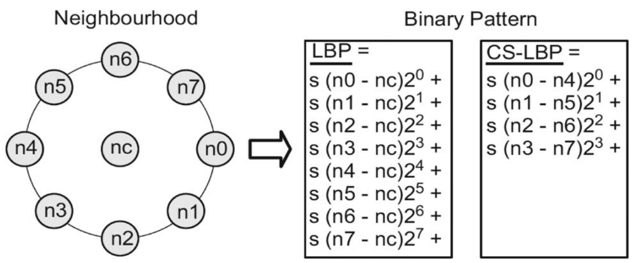

Fig. 10. LBP and CS-LBP features for a neighborhood of eight pixels [73].

i.e., low frequency, horizontal high frequency, vertical high frequency, and diagonal high frequency, as the inputs of the original LBP.

Being motivated by LBP-TOP and LGBPH, Lei *et al.* proposed to construct a third-order Gabor-image-based volume, and then, apply the original LBP to three orthogonal planes to extract the discriminative information not only in the spatial domain, but also in the Gabor-frequency and orientation domains [71]. To reduce the computation complexity, a GV-LBP operator is introduced to describe the variations in spatial-, frequency-, and orientation domains simultaneously by defining the orientation and scale neighboring points in different Gabor images.

A center-symmetric LBP (CS-LBP) [72], [73], was proposed by only comparing pairs of neighboring pixels, which are in the same diameter of the circle. This variation combines the LBP operator with the scale-invariant feature transform (SIFT) [74] definition, and thus, produces fewer binary units than the original LBP does. The difference between CS-LBP and LBP with 8 neighboring pixels is given in Fig. 10. Later, Fu and Wei [75] introduced centralized binary patterns (CBPs), making a small modification to this scheme. CBP compares the central pixel with the mean value of all the pixels in the neighborhood to produce an additional binary unit which is assigned the largest weight to emphasize the effect of the new binary bit. More recently, Huang *et al*. [76] proposed to combine the LBP and SIFT approach in a serial way: First adopted the original LBP operator on the input image using different scales to extract several MS-LBP images, and then, SIFT was applied to these resulting MS-LBP images to perform local matching.

Ahonen *et al*. proposed an approach, which is named LBP histogram Fourier features (LBP-HF) [77], to combine the LBP and the discrete Fourier transform (DFT). Unlike the existing local rotation-invariant LBP features, the LBP-HF descriptor is produced by computing an LBP histogram over the whole region, and then, constructing rotationally invariant features from the histogram with DFT. That means, rotation invariance is obtained globally and features are thus invariant to rotations of the whole input signal, but they still retain information about the relative distribution of different orientations of a uniform LBP.

IV. Local-Binary-Pattern Feature Selection

In most existing work, the input image is divided into small regions, from which LBP histograms are extracted, and the local histograms are further concatenated into a spatially enhanced feature vector of the dimensionality of O (10^3). Moreover, some recent variations even increase the feature vector length dramatically, such as ELBP, VLBP, and Gabor-wavelets-based LBP. It is believed that the derived LBP-based feature vector provides an overcomplete representation with redundant information [78], which could be reduced to be more compact and discriminative. Furthermore, when building real-time systems, it is also desired to have LBP-based representation with reduced feature length. For all the reasons, the problem of LBP feature selection has recently been addressed in many literatures. We classify these techniques into two categories: The first one is to reduce the feature length based on some rules (like uniform patterns), while the other one exploits feature-selection techniques to choose the discriminative patterns. Both streams have their own merits and drawbacks: the first one is simple, but has limited feature-selection ability; on the contrary, the second one has a better feature-selection capacity, but usually requires offline training that could be computationally expensive.

A. Rule-Based Strategy

Uniform pattern is an effective rule to select LBP features, and it has been widely adopted in this paper. In addition, there are other rules, which could be used. For instance, Lahdenoja *et al*. [79] proposed a symmetry-level scheme for uniform patterns to further reduce the length of LBP feature vectors. The symmetry level $L_{\rm sym}$ of each pattern is defined as the minimum of the total number of 1s and 0s in that pattern. For example, $L_{\rm sym}$ of both patterns, i.e., $(00111111)_2$ and $(00011000)_2$, is 2. The symmetry level is rotation invariant according to the definition. The most symmetric pattern contains the same number of 1s and 0s, which indicates a symmetric edge, while the patterns with the lowest symmetry level are the ones consisting of only 1s or 0s. It is claimed that the patterns with high symmetry level occur more frequently in the images with more discriminative power [79]. This conclusion is supported by experiments: The comparative performance was obtained by using only the patterns of high symmetry level, but the length of feature vectors was reduced by a quarter.

B. Boosting Local-Binary-Pattern Features

Boosting learning [80] provides an effective way for feature selection. In [78], by shifting and scaling a subwindow over face image, more subregions are obtained to extract local LBP histograms; the distance between the corresponding histograms of two images is utilized as the discriminative feature, and AdaBoost is used to learn a few of the most efficient features. Compared with [3], the approach achieves slightly better performance, but with fewer histograms computed from the local regions. A similar approach was also adopted in [27]. In these studies, the *n*th bin of a local histogram is utilized as a whole for region description, and feature selection is performed at region level. AdaBoost can also be exploited to learn the discriminative bins of an LBP histogram [41], since all the bins are not necessary to supply useful information. Their experiments illustrate that the selected LBP bins provide a much more compact representation with a highly reduced length of feature vector, while producing better performance. AdaBoost has been widely adopted for LBP feature selection in various tasks [18], [25], [27], [32]–[34], [47], [51], [55], [81]–[88]. Yao *et al*. [69] exploited RankBoost with domain-partitioning weak hypotheses to select the most discriminative LGBPH features.

C. Local-Binary-Pattern Subspace Learning

Subspace learning (or dimensionality reduction) [89] maps dataset from a high-dimensional space to a low-dimensional space, and thus, can be applied to LBP-based features to derive a low-dimensional compact representation. For example, Chan *et al*. introduced linear discriminant analysis (LDA) to project high-dimensional multiscale LBP features into a discriminant space [21], and the same scheme was later exploited with the multispectral LBP features calculated from color images [90]. To deal with the small sample size problem of LDA, Shan *et al*. [68] proposed an ensemble of piecewise LDA, which partitions the entire LGBP feature vector into segments and then applies LDA to each segment separately. Their approach was verified to be more effective than applying LDA to high-dimensional holistic feature vector. By combining Gabor wavelets and LBP features for face recognition, Tan and Triggs [65] first projected original feature vectors into the principal component analysis (PCA) space, and then, utilized kernel discriminative common vectors (KDCVs) to extract the discriminative features.

Dual-space LDA was also adopted to select discriminative LBP features, and proved to be effective [91]. Zhao *et al*. [92] employed Laplacian PCA (LPCA) for LBP feature selection, and their experiments showed that LPCA outperforms PCA and KPCA on selecting LBP-based feature. Wolf and Guttmann [93] adopted max-plus PCA to select LBP feature, and achieved a better performance than traditional PCA. Shan *et al*. [94] applied locality preserving projections for manifold learning. Gao and Wang [95] proposed how to select LBP feature by applying boosting learning in random subspaces. Specifically, multiple low-dimensional subspaces are randomly generated from original high-dimensional feature space as the input to boosting.

D. Other Methods

Shan *et al*. [96] adopted the conditional mutual information (CMI) maximization criterion for LBP feature selection. Their experiments show that selected LBP features perform very well. Raja and Gong [97] proposed the multiscale selected local binary feature predicates as an improvement to traditional LBP.

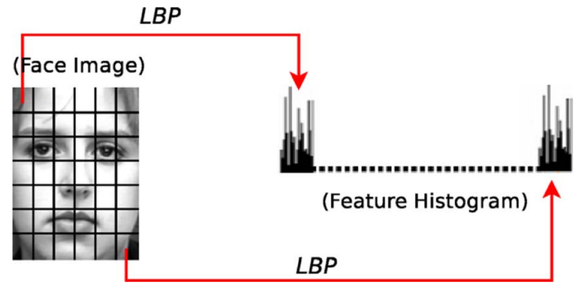

Fig. 11. LBP-based face description [27].

A feature-selection method, which is named binary histogram intersection minimization (BHIM), is introduced to generate the predicates, which comprise individual point features from multiple scales. The experiments illustrate that BHIM establishes less redundant LBP feature sets than CMI and AdaBoost do, and it produced promising performance [97]. Nanni and Lumini [98] adopted sequential forward floating selection to select the LBP feature extracted from both 2-D and 3-D images.

V. Local-Binary-Pattern-Based Facial Image Analysis

Machine-based face recognition involves two crucial aspects, i.e., facial representation [3], [63] [99]–[103] and classifier design [104]–[106]. Facial representation consists in deriving a set of relevant features from original images to describe faces, in order to facilitate effective machine-based recognition. “Good” facial features are desired to have the following properties [4]: First, they can tolerate within-class variations, while discriminate different classes well; second, they can be easily extracted from the raw images to allow fast processing; finally, they lie in a space with low dimensionality to avoid computationally expensive classifiers. Since it was introduced for face representation [3], LBP has proved to be an efficient descriptor for facial image analysis, as it fulfills the aforementioned criteria quite well, and recent years have witnessed increasing interest in LBP features for facial representation.

In this section, we first present the LBP-based facial description, and then review existing studies on different tasks, including face detection, face recognition, facial expression analysis, demographic classification, and other applications.

A. Local-Binary-Pattern-Based Face Description

A face image can be considered as a composition of the micropatterns described by LBP. One can build an LBP histogram computed over the whole-face image. However, such a representation only encodes the occurrences of micropatterns without any indication about their locations. In addition, to consider the shape information of faces, Ahonen *et al*. [3] proposed to divide face images into m local regions, from which local LBP histograms can be extracted, and then to concatenate them into a single, spatially enhanced feature histogram (as shown in Fig. 11). The resulting histogram encodes both the local texture and global shape of face images.

Most of the existing studies adopt the aforementioned scheme to extract LBP features for facial representation. However,

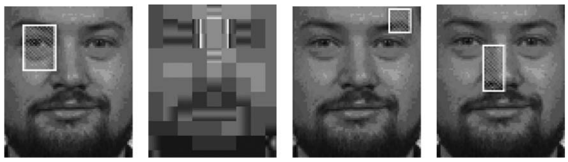

Fig. 12. Top four selected subregions [78].

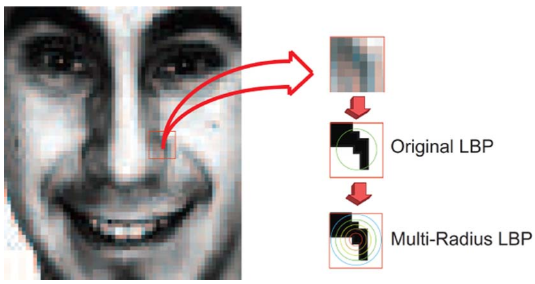

Fig. 13. Evolvement from the LBP to multi-radius LBP [64].

dividing face images into a grid of subregions is somewhat arbitrary, and the subregions are not necessarily well aligned with facial features. Moreover, the resulting facial description depends on the chosen size and the positions of these subregions. To address this issue, in [78] and [96], many more subregions are obtained by shifting and scaling a subwindow over the face images, and boost learning [80] is adopted to select the most discriminative subregions in terms of LBP histograms (as shown in Fig. 12). In their experiments, the subregions of various positions and different sizes were selected. More recently, facial representation based on LBP histograms extracted from overlapped subregions was evaluated in [31]. Furthermore, the subregions do not need to be rectangular. For example, they can also be circular [20] or triangular [107] regions.

To achieve a more comprehensive description of local facial patterns, the LBP operators with different numbers of sampling points and various neighborhood radii can be combined. For example, in [21], [64], and [108], the multiscale LBP or multiradius LBP were introduced for facial description, to reduce sensitivity of LBP-based face representations to the scale of face images (see Fig. 13). More recently, for facial expression recognition, Shan and Gritti [41] first extracted LBP features of different scales, and then, ran AdaBoost to learn the most discriminative features. It proved that a boosted classifier of multiscale LBP consistently outperforms that of single-scale LBP, and the selected LBP bins are distributed at all scales on the Cohn–Kanade database.

B. Face Detection

The purpose of face detection is to determine the locations and sizes of human faces in digital images. Hadid *et al*. [4] first used LBP for face detection. To describe low-resolution faces, a four-neighborhood LBP operator $\mathrm{LBP}_{(4,1)}$ was applied to overlapping small regions. The support vector machine (SVM) classifier was adopted to discriminate faces from nonfaces. To compare with the state-of-the-art methods, they performed their experiments on the MIT-CMU dataset, and the proposed method detected 221 faces without any false positives. Later, they [109] proposed a hybrid method to address face detection under unconstrained environments. Their method first searched for the potential skin regions in an input image to avoid scanning the entire image, as was done in [110]. Then, a coarse-to-fine strategy is employed to determine whether the scanned regions are faces or not: In the coarse stage, LBP feature vector extracted from the whole region is utilized as the input to a polynomial SVM; patterns that are not rejected by the first SVM classifier are further analyzed by the second finer one whose inputs are extracted from overlapped blocks inside the region. The detection rate reported is 93.4% with 13 false positives.

Being motivated by the fact that LBP is invariant to monotonic transformations, Zhang and Zhao [19] proposed to compute the spatial histograms on color measurements for face detection in color images. After extracting five measurements, Y, R, G, B, and θ, in the RGB and YUV color space from the original images, LBP was utilized to transform the obtained measures to histograms, which are computed as facial description with 23 different spatial templates to preserve the shape information of faces. A hierarchical classifier combining histogram matching and SVM was used to discriminate between faces and nonfaces. The experiments were conducted on 251 color images, including 356 frontal faces with variations in color, position, size, and expression, and precision of 91.7% was reported. Jin *et al*. [17] exploited ILBP features for facial representation, and modeled faces and nonfaces using the multivariable Gaussian distribution. Given the ILBP-based features of an input image, the likelihood of the face class and nonface class is calculated separately; the Bayesian decision rule is then applied to decide whether the image is a face or not. The Yale B and MIT-CMU databases were used for evaluation, and the detection rate was more than 90% with a false-positive rate of 2.99×10^{-7}. They later extracted ILBP-based features from larger neighborhoods [47], and trained a cascade AdaBoost detector, which achieved detection result of 93.0% on the MIT-CMU database, and 94.6% on the Yale B database. Zhang *et al*. [18] exploited MB-LBP for face detection. Performing experiment on a dataset containing 13 000 faces and 50 000 nonfaces with a false-alarm rate set to 0.001, the MB-LBP-based approach achieved superior accuracy, which was 15% higher than Haar-like features and 8% higher than original LBP features. The experiments on the MIT-CMU database also showed that the approach displayed a comparable performance with that in [80] but with fewer features.

C. Face Recognition

Face recognition aims to identify or verify a person from a digital image or a video sequence. Ahonen *et al.* [3] introduced LBP in face recognition with nearest neighbor (NN) classifier and chi-square distance as the dissimilarity measure. The experimental results showed that their approach outperforms the PCA, the elastic bunch graph matching (EBGM), and the Bayesian intra-/extrapersonal classifier on all four probe sets of the FERET database. They later investigated whether these good results are due to the use of local regions or the discriminative capacity of LBP methodology [111]. Based on the comparisons with three other texture descriptors extracting features from the same local patches, the strength of LBP to represent faces was clearly confirmed. In [4], face recognition experiments were also carried out on the MoBo database, which is quite challenging, since the images are in low resolution. As mentioned earlier, AdaBoost later was applied to select a few of the most effective LBP-based features for face recognition [78]. Compared with the approach in [3], the boosting LBP-based method achieves a slightly better recognition rate, while using fewer LBP features.

Zhang *et al.* [24] introduced MHLVP for face recognition based on histogram intersection. Their experiments on FERET database showed that their algorithm provides better accuracy than some milestone approaches, which contains the best ones in FERET'97. In particular, they achieved 95.9% accuracy on the *fc* set with illumination changes. They employed LGBPHS [67], which is similar to MHLVP but with weighted rules, for the same task. In addition to the FERET dataset, they also ran experiments on the AR database. The results on both databases were very promising. Furthermore, they [68] exploited LGBP with an ensemble of piecewise LDA, which not only reduces the feature dimension, but also improves the performance on the FERET database. Yao *et al.* [69] adopted the domain-partitioning to select LGBPH features for face recognition. The subsets *fb* and *Dup I* from the FERET database were used to evaluate the approach, and comparable results were achieved with only 50 selected features. Zhang *et al.* [112] argued that Gabor phases are also useful for face recognition. By encoding Gabor phases through LBP and forming local feature histograms, impressive recognition rates were obtained on FERET database (99% for *fb*, 96% for *fc*, 78% for *Dup I*, and 77% for *Dup II*).

Zhao *et al.* [26] applied kernel LDA with the LBP features for face recognition, where their kernel function was designed using the chi-square distance and radial basis function. Their method has been proved effective on FRGC Exp2.0.1, which achieves a verification rate of 97.4% with false acceptance rate (FAR) at 0.001, and 99.2% with FAR at 0.01. Rodriguez and Marcel [113] proposed an LBP-based generative method for face authentication. Specifically, LBP histogram is interpreted as a probability distribution, and a generic face model is considered as a collection of LBP histograms. A client-specific model is then obtained by maximum *a posteriori* (MAP) from a generic face model. The outcomes on XM2VTS and BANCA, reveals that their approach outperforms the approaches in [3] and [78].

Li *et al.* [25] designed a framework to fuse 2-D and 3-D face recognition based on LBP features at both feature and decision levels. AdaBoost was used for LBP feature selection. The experiments on a database containing 252 subjects illustrate the advantages of two-level fusion over decision-level fusion. To our knowledge, this is the first study to apply LBP to 3-D domain. Later, Huang *et al.* [52] extended LBP to 3-D-LBP, which is actually similar to ELBP, as in [51], for 3-D face recognition based on range images; their approach achieved the promising result of 9.4% Energy efficiency ratio (EER) on FRGC v2.0 Exp3. ROC I. Nanni and Lumini [98] also utilized LBP to extract both 2-D and 3-D facial features; their experiments were conducted on a subset of 198 persons from the Notre-Dame database collection D; the reported EER was 3.5%.

Li *et al.* [114], [115] later applied LBP to near-IR (NIR) facial images to obtain robust facial descriptions under illumination variations. The method achieved a verification rate of 90% at FAR = 0.001, and 95% at FAR = 0.01 on a database with 870 subjects. The same method was utilized with enhanced NIR images for face verification outdoor, especially in sunlight [83]. Pan *et al.* [86] proposed to improve the robustness of this study to variations of pose. NIR face images were decomposed into several parts in accordance with key facial components, and LBP features extracted from these parts were selected by AdaBoost; the outputs of part classifiers were then fused to give the final score. The verification rate of their approach is 96.03% with FAR = 0.001. Huang *et al.* [51] adopted AdaBoost to learn ELBP features for NIR face recognition, and obtained a recognition rate of 95.74% on a database with 60 individuals.

Yan *et al.* examined multiradius LBP for face recognition [64]. Their experiments on Purdue (90 subjects) and CMU-PIE (68 subjects) datasets showed that LBP and Gabor features are mutually complementary and a combination of similarity scores can bring performance improvement. Chan *et al.* [21] employed the multiscale LBP with LDA for face recognition. The reported performance on the FERET and XM2VTS databases was better than the state-of-the-art approaches. In addition, they projected multispectral LBP features extracted from local regions into an LDA subspace as the discriminative regional description. They proved the effectiveness of their method on the FRGC and XM2VTS databases. Hadid *et al.* [82], [85] introduced VLBP to extract local facial dynamics for spatiotemporal face recognition from video sequences. AdaBoost was applied to learn the specific facial dynamics of each subject from the LBP-based features, while ignoring intrapersonal temporal information, such as facial expressions. Their approach achieved superior performances on various databases: MoBo (97.9%), Honda/UCSD (96.0%), and CRIM (98.5%). Lei *et al.* [71] used GV-LBP-TOP- and E-GV-LBP-based features for face recognition, and both methods achieved encouraging results on FERET and FRGC2.0 databases. Yang and Wang [50] introduced Hamming LBP for face recognition on the FRGC dataset. The experimental results reveal that the Hamming LBP outperforms the original LBP, especially when variations of illumination and facial expression exist. Liao and Chung [23] exploited elongated LBP to capture the anisotropic structures of faces. Average maximum distance gradient magnitude was proposed to embed the information on gray-level difference between the reference and the neighboring pixel in each elongated LBP pattern. With a subset of 70 persons randomly selected from the FERET database, their method obtained 93.16% accuracy, and 98.50% on the ORL database.

Tan and Triggs [22] proposed a method for face recognition under illumination variations, which includes preprocessing to reduce sensitivity to illumination changes, and LTP to solve the problem caused by LBP's sensitivity to random and quantization noise. A distance transform-based similarity metric was used for decision. The method showed promising performance on three datasets with illumination variations: FRGC Exp 1.0.4 (86.3%), Yale-B (100%), and CMU PIE (100%). In addition,

TABLE II
PERFORMANCE COMPARISON OF LBP-BASED FACE RECOGNITION ON THE FERET DATABASE

Author, Year, Reference	Facial Feature	Core Matching Algorithm	Reported Accuracy
Ahonen 2004 [3, 23]	$LBP^{U2}_{(8,2)}$	Weighted χ^2	fb 0.970, Dup I 0.660, fc 0.790, Dup II 0.640.
Zhang 2004 [39]	Boosting LBP	χ^2	fb 0.979
Zhang 2005 [27]	MHLVP	Histogram Intersection	fb 0.942, Dup I 0.676, fc 0.959, Dup II 0.594.
Zhang 2005 [74]	LGBPHS	Weighted Histogram Intersection	fb 0.980, Dup I 0.740, fc 0.970, Dup II 0.710.
Shan 2006 [40]	LGBP	EPFDA	fb 0.996, Dup I 0.920, fc 0.990, Dup II 0.889.
Yao 2007 [75]	LGBPH	CDP-RankBoost	fb 0.970, Dup I 0.550.
Chan 2007 [24]	Multi-Scale LBP	LDA	fb 0.986, Dup I 0.722, fc 0.711, Dup II 0.474.
Tan 2007 [72]	Gabor+LBP	KDCV	fb 0.980, Dup I 0.900, fc 0.980, Dup II 0.850.
Liao 2007 [26]	Elongated LBP	AMDGM	0.9316 (only 70 samples for test)
Zhang 2008 [111]	ELGBP (Mag + Pha)	Weighted Histogram Intersection	fb 0.990, Dup I 0.780, fc 0.960, Dup II 0.770.
Lei 2008 [77]	E-GV-LBP	Weighted Histogram Intersection	0.8873 (all four probe together)

they fused Gabor and LBP features to construct heterogeneous features for face recognition in [65]. With the features extracted by KDCV, they achieved satisfying results on the FRGC 1.0.4, FRGC 2.0.4, and FERET databases. Park and Kim [116] presented an adaptive smoothing approach for face image normalization under changing lighting. The illumination is estimated by iteratively convolving the input image with a 3×3 averaging kernel weighted by a simple measure of illumination discontinuity at each pixel. In particular, the kernel weights are encoded into an LBP to achieve fast and memory-efficient processing. Six hundred thirty-three frontal face images were selected from the Yale B database, and average recognition accuracy was 99.74% with 0.038 s time consumed for each image.

Table II summarizes the performance of different approaches on the FERET database.

D. *Facial Expression Analysis*

Machine-based facial expression recognition aims to recognize facial affect states automatically, and may depend on both audio and visual clues [117]. In this paper, we focus our attention on studies purely based on visual information, which use facial motion or facial features [118], [119]. Most of these studies only consider the prototypical emotional states, which include seven basic universal categories, namely, neutral, anger, disgust, fear, happiness, sadness, and surprise.

Feng *et al*. [28], [120] exploited a coarse-to-fine classification scheme with LBP for facial expression recognition by making use of images. More precisely, at the coarse stage, a seven-class problem was first reduced to a two-class one, while at fine stage, a k-NN classifier performed the final decision. Their approach produced 77% average recognition accuracy on JAFFE dataset. In [121]–[123], with the same facial description, a linear programming technique was applied for expression classification. A seven-class problem was decomposed into 21 binary classifications by using the one-against-one scheme. With this method, they obtained over 90% accuracy both on the JAFFE database and some real videos.

Shan *et al*. [124] also investigated LBP for facial expression recognition. The template matching with weighted chi-square statistics and SVM were adopted to classify the basic prototypical facial expressions, and the best performance obtained on the Cohn–Kanade Database reached 88.4% by using SVM. In many applications, which involve facial expression recognition, the input face images are with low resolution. In [124] and [125], they further studied this topic. They not only performed evaluation on face images with different resolutions, but also ran experiments on real-world low-resolution video sequences. It was observed that LBP features perform stably and robustly over a useful range of face images with low resolutions. Shan *et al*. [96] introduced CMI maximization criterion for LBP feature selection, and the selected features improved recognition accuracy compared with that using AdaBoost. Later, Shan *et al*. [94] also studied facial expression manifold learning by embedding image sequences in a high-dimensional LBP space to a low-dimensional manifold. Their experiments on the Cohn–Kanade database illustrated that meaningful projections could be obtained. Shan and Gritti [41] used AdaBoost to learn a set of discriminative bins of an LBP histogram for facial expression recognition. Their experiments indicated that the selected bins provide a much more compact facial description. In addition, it was evidenced that it is necessary to consider the multiscale LBP for facial description. By applying SVM to the selected multiscale LBP bins, they obtained recognition rate of 93.1% on the Cohn–Kanade database, comparable with the best results so far reported on this database.

He *et al*. [70] used LBP on four kinds of frequency images decomposed by Gabor wavelets for facial expression recognition. Their approach provided better performance than LBP did on the JAFFE dataset. To consider multiple cues, Liao *et al*. [29] extracted $\mathrm{LBP}^{ri}_{(P,R)}$ features in both intensity and gradient maps, and then, computed the Tsallis entropy of the Gabor filter responses as the first feature set and performed null-space LDA for the second feature set. With the SVM classifier, they achieved 94.59% accuracy for images of 64 × 64 pixels, and 84.62% for 16 × 16 pixels on the JAFFE database. With an active appearance model, Feng *et al*. [126] extracted the local texture feature by applying LBP to facial feature points; the direction between each pair of feature points was also considered as shape information. In addition, they used LBP with the entire image to get global texture information. Combining these three types of feature, an NN-based classifier with weighted chi-square statistic was introduced for classification. Subject-independent recognition rate of 72% was reported on the JAFFE dataset. Cao *et al*. [127] combined LBP with embedded hidden Markov model to recognize facial expressions by using an active shape model (ASM), and achieved 65% accuracy on the JAFFE dataset.

Zhao and Pietikäinen [30], [60] employed VLBP and LBP-TOP for facial expression recognition in video sequences. A recognition rate of 96.26% was achieved on the Cohn–Kanade database; the evaluation over a range of image resolutions and frame rates demonstrated that both approaches outperform the state-of-the-art methods. In addition, they compute the LBP-TOP at multiple resolutions to describe dynamic events [87]. AdaBoost technique was used to learn the principal appearance and motion from the spatiotemporal descriptors. Fu and Wei [75] utilized the CBP instead of LBP for facial expression recognition, and recognition rates of 94.76% and 94.86% were achieved on the JAFFE and Cohn–Kanade databases, respectively. The capacity of LBP to describe faces was further demonstrated in [31], where Gritti *et al*. compared different local features: LBP, LTP, histogram of oriented gradients [128], and Gabor wavelets, with various parameter settings for facial expression recognition. On the basis of their experiments, LBP with an overlapping strategy achieved the best result, 92.9%, on the Cohn–Kanade database. Furthermore, it was indicated that the overlapping LBP is the most robust to deal with registration errors.

E. Demographic Classification and Other Applications

Demographic classification is used to classify age, gender, and ethnicity, based on face images. Sun *et al*. [32] adopted the boosting-LBP-based approach [78] for gender recognition, and obtained the performance of 95.75% on the FERET dataset. In [129] and [130], Lian and Lu combined the LBP-based facial description with SVM for multiview gender classification and reported an average accuracy of 94.08% on the CAS-PEAL face dataset. Yang and Ai [33] exploited the LBP-based features for a face-based demographic classification, which involved gender, ethnicity, and age classification. Given a local patch, chi-square distance between achieved LBP histograms was utilized as a confidence measure for classification. The positive mean histogram was utilized for initialization, and the steep descent method was applied to find an optimal reference template. They adopted the Real AdaBoost to train a strong classifier. The achieved error rates for gender classification on the FERET, PIE, and a snapshot database were 6.7%, 8.9%, and 3.68%, respectively. Their method also produced promising performance for ethnicity and age classification.

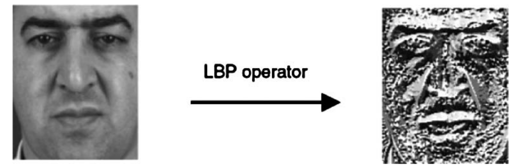

Fig. 14. Original image (left) processed by the LBP operator (right) [132].

Huang *et al*. [108] proposed an improved ASM framework, namely, ELBP-ASM, in which local appearance patterns of key points are modeled by the ELBP. The experiments on a dataset with 250 samples show that ELBP-ASM achieves more accurate results than the original ASM. In order to extend ASM to improve robustness against illumination variations, Marcel *et al*. [131] later presented a divided-square-based LBP-ASM to extract histograms from a square region divided into four blocks around each landmark instead of the normal profile. Histograms were then concatenated into a single-feature vector, which represents local appearance. The comparative experiments on XM2VTS dataset showed that this method outperforms ELBP-ASM [108] and requires only raw images for facial keypoint localization.

In [35], Ma *et al*. introduced the LGBP to encode the local facial characteristics for head pose estimation. With an SVM classifier, estimation rate of 97.14% for seven poses was gained on a subset of the CAS-PEAL dataset that contains 200 subjects. Cao *et al*. [34] used a facial-symmetry-based approach to standardize the face image quality. With this method, facial asymmetries caused by nonfrontal illumination and improper facial pose can be measured. The effectiveness was evaluated on images of ten persons of the Yale B dataset.

LBP can also be used as a preprocessing technique on face images. For instance, Heusch *et al*. [132] considered LBP as a preprocessing step to remove lighting effects (see Fig. 14). Compared with other preprocessing methods, including histogram equalization and the technique proposed by Gross and Brajovic [133], LBP provided better results on the XM2VTS database. Cardinaux *et al*. showed that LBP is better combined with feature-based HMM than with appearance-based LDA for face recognition on the BANCA dataset [134]. Poh *et al*. presented a similar comparative study in [135], and their experiments further supported that LBP is effective for face preprocessing, but the combination of LBP with feature-based Gaussian mixtures models did not perform as well as the combination with LDA. The use of LBP for preprocessing was also addressed in [48]; a comparative study on five preprocessing in 16 different

Eigenspace-based recognition systems evidenced that MLBP achieves promising results for illumination compensation and normalization. More recently, in order to highlight the details of facial images, Huang *et al*. [136], [137] proposed to use LBP to extract range and texture LBP faces, and canonical correlation analysis was then applied to learn the relationship between the two types of LBP faces for asymmetric face recognition. The reported result was 95.61% on the FRGC v2.0 dataset [137].

F. Face Analysis Systems

Advantages of LBP make it very attractive to build real-time face analysis systems. Furthermore, related hardware designed for high-speed LBP computation [138]–[141] also boosts the development of LBP-based real-world applications.

Hadid *et al*. built an access control system by using LBP-based face recognition [142]. In their system, a camera was set on a door to capture video frames; LBP features were extracted for both background subtraction and face recognition. The face detection approach in [110] was adopted for face detection in color images, and the face recognition method in [3] was applied for person identification. The face recognition accuracy of 71.6% was obtained on 20 video sequences of ten subjects.

Trinh *et al*. [143] presented a system to detect multiple faces in video sequences, where faces are not limited to frontal views. An adaptive selection approach from two skin models in RGB and ratio RGB spaces is used to overcome the illumination problem by automatic focus of the camera. The experimental result of 93% accuracy was reported on the NRC-IIT database, which consists of 23 single-face video sequences of 11 persons with different poses. The system runs at 2.57 f/s for image sequences of 320×240 pixels on a standard PC (Pentium 4, 2.6-GHz, 512-MB RAM) in the Visual C++ environment.

Based on the LBP features extracted from NIR faces, Li *et al*. [114], [115] designed an illumination-invariant face recognition system for cooperative users in an indoor situation. AdaBoost was used to learn Haar features for face detection and eye detection, and to select LBP features for face recognition. All three parts achieve outstanding results with low cost on a large dataset. The system can operate in real time with an EER below 0.3%.

Ekenel *et al*. [144] introduced a portable face recognition system, which is deployed on a laptop using a standard webcam for image acquisition. On the basis of the relevant regions determined by skin color, the two eyes were first detected with a cascade AdaBoost classifier of Haar features. These were then used to register face images. LBP was used to preprocess facial regions to reduce illumination influences. Their system was evaluated on a small dataset consisting of 42 sequences from 14 subjects, and produced 79% accuracy.

Hadid *et al*. [145] implemented face detection and authentication on mobile phones equipped with an ARM9 processor. Cascade AdaBoost with Haar features was applied for face and eye detection, while LBP was exploited for face authentication. Although the CPU and memory capabilities of mobile phones are limited, the experiments showed encouraging performance on face detection, and displayed recognition rates of 82% for faces of 40×40 pixels and 96% for faces of 80×80 pixels. The system ran at 2 f/s on video sequences with a resolution of 320 $\times$ 240 pixels. Abbo *et al*. [146] recently mapped an LBP-based facial expression recognition algorithm proposed in [124] on a low-power smart camera, which was assembled with a massively parallel processor for low-level and intermediate vision processing, and an 8051 microcontroller for high-level decision making and the camera control tasks.

Hannuksela *et al*. [88] proposed a head-tracking system to control the user interface on hand-held mobile devices. Face and eye detection were realized using boosting-LBP approach. It worked in real time on a resource-limited mobile device. In an interactive photo-annotation system [147], LBP was also used to extract facial features for face clustering and reranking.

G. Discussion

The techniques developed so far for facial representation can be roughly classified into two main categories: holistic-based ones and local-based ones [148], [149]. The holistic approaches use the whole facial region to construct a subspace using, e.g., PCA [99], LDA [100], independent component analysis [150], or locally linear embedding [151]. On the other hand, the local-based ones, e.g., [63], [101], and [152], proceed first to locate a number of features or components from a face, and then, classify them by combining and comparing with corresponding local statistics. The local approaches have shown promising performances in recent years. It has been proved by Heisele *et al*. [153] that the component-based face recognition methods (local-feature-based) perform better than the global ones (holistic-based). The main reason is that holistic approaches require face images to be accurately normalized with regard to pose, illumination condition, and scale. In addition, global features are also more sensitive to facial expression variations and occlusions. Since the local feature-based methods extract features from local points or patches, there always remain some invariant features, even in the presence of facial expression or occlusion variations, and recognition can still be achieved by matching remaining invariant features. Therefore, the local-feature-based methods are potentially more robust than holistic ones to facial expression changes and occlusions. Moreover, unlike holistic approaches, they require few samples for enrollment, and can even achieve analysis with a single face image in the gallery set [154]. From this viewpoint, if LBP is used in a straightforward manner as a global representation, it is its local- or component-oriented variants that prove to be efficient descriptors for facial image analysis as the earlier overview highlights. This motivates increasing interests in LBP-based features for facial representation, since it was applied for face representation [3].

Compared with other popular local descriptors, as discussed in [148], [155], [156], namely, Gabor wavelets [63], [157]–[159] and SIFT [101], [155], Luo *et al*. [155] showed that SIFT is not as robust as LBP to illumination effects for face recognition on the FERET dataset. Zou *et al*. [148] compared Gabor wavelets and LBP by using the same database for the same task, and concluded that Gabor wavelets are more insensitive to illumination changes, since they detect amplitude-invariant spatial frequencies of gray values of pixels, while LBP is greatly affected by nonmonotonic gray-value transformations. Ruiz-del-Solar *et al*. [156] evaluated these three methods extensively for face recognition not only on controlled datasets, e.g., FERET and FRGC, but also on the UCH FaceHRI database, which is designed for human–robot interaction as well as the LFW dataset, captured in unconstrained environments. With regard to robustness-to-illumination variations, their study illustrated that Gabor wavelets achieved the best performance on the FERET database, LBP was not far behind, while SIFT was the last, thus further supporting the earlier conclusions. On the UCH FaceHRI database, the LBP approach gained the best results in all the specially designed experiments with indoor and outdoor lighting, expression, scaling, and rotation, followed by Gabor wavelets and SIFT. On the LFW dataset, LBP and Gabor wavelets obtained a slightly better result than each other with aligned face and nonaligned face, respectively, both of which surpassed that of SIFT. On the other hand, in their investigation on computation cost, LBP ran much faster than Gabor wavelet and SIFT.

VI. Concluding Remarks

LBP is one of the most powerful descriptors to represent local structures. Due to its advantages, i.e., its tolerance of monotonic illumination changes and its computational simplicity, LBP has been successfully used for many different image analysis tasks, such as facial image analysis, biomedical image analysis, aerial image analysis, motion analysis, and image and video retrieval.

During the development of LBP methodology, a large number of variations are designed to expand the scope of application, which offer better performance as well as improve the robustness in one or more aspects of the original LBP. ILBP, Hamming LBP, and ELBP enhance the discriminative ability of LBP; LTP and SLBP focus on improving the robustness of LBP on noisy images; MB-LBP, elongated LBP, TPLBP, and FPLBP, change the scale of LBP to provide other categories of local information; Gabor-wavelet-based LBP, CS-LBP, and LBP-HF combine other methods with LBP to bring in new merits. However, the earlier extensions only operate on traditional 2-D data; the variant 3-DLBP and VLBP should be highlighted, since both of them expand the scope of LBP applications: 3-DLBP extends the LBP operator to describe 3-D volume data, while VLBP endows LBP with the ability to capture dynamic information.

To obtain a small set of the most discriminative LBP-based features for better performance and dimensionality reduction, LBP-based representations are associated with some popular techniques of feature-selection schemes to reduce the feature length of LBP codes, which contain rule-based strategy, boosting and subspace learning, etc.

As the most typical and important application of LBP, facial image analysis provides a very good demonstration of the use, development, and performance of LBP. From this comprehensive overview, following conclusions can be drawn: 1) local- or component-oriented LBP representations are effective representations for facial image analysis, as they encode the information of facial configuration while providing local structure patterns; and 2) using the local- or component-oriented LBP facial representations, feature selection is particularly important for various tasks in facial image analysis, since this facial description scheme greatly increases the feature length.

Meanwhile, similar to most of the texture-based techniques, LBP is sensitive to severe lighting changes, and to blurred and noisy images [39]. The former case can be regarded as nonmonotonic lighting variations, which normally occur in facial images due to 3-D facial volume structures, thereby leading to nonmonotonic transformations, e.g., shadows and bright spots can typically occur and change their positions depending on lighting directions. While the latter case is often caused by the bad quality of camera sensors and poor user cooperation of capture condition, etc. As a result, in such environments, it is necessary and useful to preprocess the images before applying LBP.

In addition, some open questions for subregion-based LBP description, e.g., facial description, concern the relevant number of components and the corresponding neighborhood of a certain LBP operator for the best analysis result. Although these questions have been discussed in several papers, and even with machine-learning techniques, these conclusions drawn so far have always been dependent on the used databases and some given parameters.

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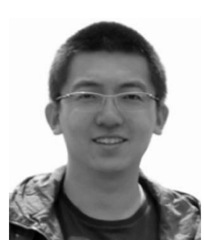

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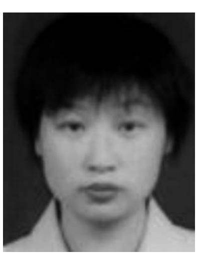

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