EXTENDED LOCAL BINARY PATTERN FUSION FOR FACE RECOGNITION

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ABSTRACT

This paper presents a simple, novel, yet highly effective approach for robust face recognition. Given LBP-like descriptors based on local accumulated pixel differences, Angular Differences (AD) and Radial Differences (RD), the local differences are decomposed into complementary components of signs and magnitudes. The proposed descriptors have desirable features: (1) robustness to lighting, pose, and expression; (2) computation efficiency; (3) encoding of both microstructures and macrostructures; (4) consistent in form with traditional LBP, thus inheriting the merits of LBP; and (5) no required training, improving generalizability.

From a given face image, we obtain six histogram features, each of which is obtained by concatenating spatial histograms extracted from nonoverlapping subregions. The Whitened PCA technique is used for dimensionality reduction, followed by Nearest Neighbor classification.

We have evaluated the effectiveness of the proposed method on the Extended Yale B and CAS-PEAL-R1 databases. The proposed method impressively outperforms other well known systems, including what we believe to be the best reported performance for the the CAS-PEAL-R1 lighting probe set with a recognition rate of 72.3%.

***Index Terms*—** Face recognition, Feature extraction, Local binary pattern, Local descriptors

1. INTRODUCTION

Face recognition, as one of the most successful applications of image analysis and understanding, has received considerable attention in the past decades due to its challenging nature and to its vast range of applications, with excellent surveys given in [1]. Nevertheless it remains a great challenge to design good face descriptors which achieve the three competing goals of computational efficiency, discriminability, and robustness to intraperson variations (including changes in illumination, pose, expression, age, blur and occlusion).

Recently, local feature descriptors for face recognition have attracted increasing attention and have achieved excellent performance. Among the local feature based approaches, Local Binary Patterns (LBP) have emerged as one of the most prominent face analysis method since the pioneering work by Ahonen *et al.* [2]. A number of LBP variants have been presented for face recognition, noticeable examples including the Local Gabor Binary Pattern Histogram Sequence (LGBPHS) method [3] and the Histogram of Gabor Phase Patterns (HGPP) [4]. There have been three very recent LBP-related approaches: the POEM by Vu *et al.* published in 2012 [5], which computes LBP-like features from SIFT histograms; the LQP by Hussain *et al.* published in 2012 [6], which first learns significant LQP patterns globally with KMeans clustering and then uses them to encode the face images; and the Discriminant Face Descriptor (DFD) by Lei *et al.* published in 2013 [7], which works quite well in face identification and verification, however it is quite complex, involves a number of parameters, has high dimensionality, and requires a time consuming training process with sufficient training data for stability.

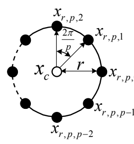

Fig. 1. Central pixel x_c and its p circularly and evenly spaced neighbors on a circle of radius r.

LBP encodes only the relative intensity relationships between a pixel and its neighbors. Our focus is on LBP-like feature extraction, exploiting the complementary information contained by pairwise pixel comparisons between neighboring pixels. In particular, we are motivated by our recent work on texture classification [8], where four LBP like descriptors — Center Intensity based LBP (CI-LBP), Neighborhood Intensity based LBP (NI-LBP), Radial Difference based LBP (RD-LBP) and Angular Difference based LBP (AD-LBP) — were proposed, as were the multiscale joint histogram features of CI-LBP, NI-LBP and RD-LBP, which were found to be highly effective for rotation invariant texture classification.

In this paper we intend to extend the idea behind the work in [8] to the face recognition problem by proposing a more generalized formulation, the Extended Local Binary Pattern (ELBP). The remainder of this paper is organized as follows: Section 2 presents the details of our proposed extended LBP like descriptors and the face recognition pipeline, and experimental results are presented in Section 3.

2. EXTENDED SET OF LBP DESCRIPTORS

2.1. A Brief Review of LBP

LBP characterizes the spatial structure of a local image texture by thresholding a 3×3 square neighborhood with the value of the center pixel and considering only the sign information to form a local binary pattern. A more general formulation defined on a circular

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symmetric neighborhood was proposed in [9] that allowed for multi-resolution analysis and rotation invariance.

Formally, given a pixel x_c in the image, the LBP pattern is computed by comparing its value with those of its p neighboring pixels

$$\underline{\boldsymbol{x}}_{r,p} = [x_{r,p,0}, \ldots, x_{r,p,p-1}]^T$$

that are evenly distributed in angle on a circle of radius r centered on x_c, as in Fig. 1, such that the LBP response is calculated as

$$\mathrm{LBP}_{r,p} = \sum_{n=0}^{p-1} s(x_{r,p,n} - x_c)2^n, \quad s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{1}$$

where $s()$ is the sign function. Relative to the origin of the center pixel x_c, the coordinates of the neighbors are given by $-r\sin(2\pi n/p), r\cos(2\pi n/p)$. The gray values of neighbors which do not lie exactly at a pixel location are estimated by interpolation.

In order to reduce the dimensionality of the original descriptor $\mathrm{LBP}_{r,p}$, Ojala *et al.* [9] introduced the so called uniform LBP operator, denoted as $\mathrm{LBP}_{r,p}^{u2}$, which is a preferable choice for the face recognition problem [2]. However, changes in p may cause big differences in the length of the feature vector. As recommended by Ahonen [2], the $\mathrm{LBP}_{r,8}^{u2}$ operator is selected for face recognition since it is a good trade-off between recognition performance and feature vector length. In our ELBP approach, presented in this paper, the traditional $\mathrm{LBP}_{r,p}$ descriptor is adopted as one member and is renamed as $\mathrm{LBP\_S}_{r,p}$, representing the sign component of the local differences.

More recently, Guo *et al.* [10] proposed a complete LBP for texture classification, which includes both the sign and the magnitude components between a given central pixel and its neighbors in order to improve the discriminative power of the original LBP operator. The operator derived from the sign component is the same as the original LBP operator defined in (1). The operator computed from the magnitude component, denoted as LBP_M, performs a binary comparison between the absolute value of the difference between the central pixel and its neighbors and a global threshold to generate an LBP-like code:

$$\mathrm{LBP\_M}_{r,p} = \sum_{n=0}^{p-1} s(|x_{r,p,n} - x_{0,0}| - \mu_{r,p})2^n \tag{2}$$

where $\mu_{r,p} = \frac{1}{p}\sum_{n=0}^{p-1} |x_{r,p,n} - x_{0,0}|$. Here $\mu_{r,p}$ is different from the the global threshold used in [10]. The $\mathrm{LBP\_M}_{r,p}$ descriptor defined in equation (2) is also adopted as one member in our ELBP.

2.2. Angular Differences-Based Descriptors

LBP encodes only the relationship between a central point and its neighbors. Although it has been extended to facilitate analysis of image textures at multiple scales [9] by varying the sampling radius r and the number of sampling points p, important information regarding the relationship between neighboring points on the same radius (intra-radius) and the relationship between neighboring points across different radii (inter-radius) is lost.

As a parallel development to the intensity descriptors just developed, we also propose pixel *differences* in radial and angular directions on a circular grid, different from the traditional pixel differences which are computed in horizontal and vertical directions. More specifically, we propose two families of related descriptors, the Angular Difference-based Local Binary Pattern (ADLBP) and the Radial Difference-based Local Binary Pattern (RDLBP), designed to encode additional types of local texture information. Similar to LBP_S and LBP_M, both the sign and magnitude components of angular and radial differences will be considered, leading to a total

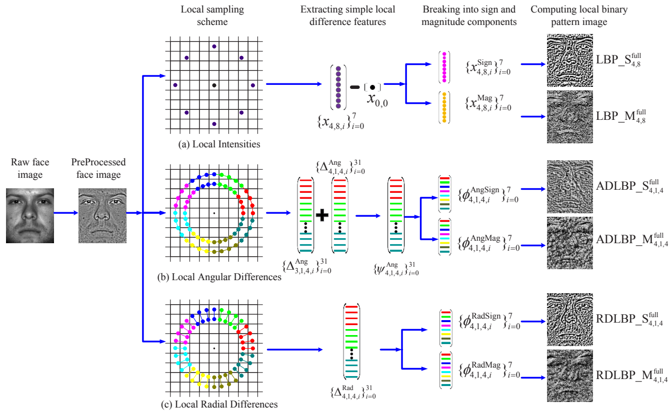

Fig. 2. The proposed extended set of LBPs are built up of three classes: (a) Intensity based LBPs, (b) Angular difference based LBPs, and (c) Radial difference based LBPs.

of four different descriptors ADLBP_S, ADLBP_M, RDLBP_S and RDLBP_M, as illustrated in Fig. 2. The proposed new descriptors are not so much competitive with traditional LBP, rather complementary. We first introduce the derivation of the angular-difference descriptors ADLBP_S and ADLBP_M, and then introduce RDLBP_S and RDLBP_M in Section 2.3.

For each pixel in the image, we consider the accumulated angular differences computed from its neighbors distributed uniformly in the ring of radius r. Similar to the sampling scheme in the original LBP approach, we sample pixels around a central pixel, however on any circle of radius r we restrict the number of points sampled to be a multiple of eight, thus $p = 8q$ for some positive integer q, controlling the number of sampling points on radius r. Thus the neighbors of $x_{0,0}$ sampled on radius r are $\underline{\boldsymbol{x}}_{r,8q} = [x_{r,8q,0}, \cdots, x_{r,8q,8q-1}]^T$.

Motivated by the success of the radial difference descriptor in [8], we consider averaging angular differences over more than one radius. Empirical tests suggest that averaging over two adjacent radii produces the best results, so the ADLBP_S descriptor is computed by accumulating the angular differences of radii r and $r-1$:

$$\underline{\psi}_{r,\delta,q} = \underline{\Delta}^{\mathrm{Ang}}_{r,\delta,q} + \underline{\Delta}^{\mathrm{Ang}}_{r-1,\delta,q} \tag{3}$$

where

$$\underline{\Delta}^{\mathrm{Ang}}_{r,\delta,q} = [\Delta^{\mathrm{Ang}}_{r,\delta,q,0}, \cdots, \Delta^{\mathrm{Ang}}_{r,\delta,q,8q-1}]^T \tag{4}$$

$$\Delta^{\mathrm{Ang}}_{r,\delta,q,n} = x_{r,p,n} - x_{r,p,\mathrm{mod}(n+\delta,p)} \tag{5}$$

where the latter term $\Delta^{\mathrm{Ang}}_{r,\delta,q,n}$ is the angular difference computed with given angular displacement $\delta(2\pi/p)$, where δ is an integer such that $1 \leq \delta \leq p/2$. $x_{r,p,n}$ and $x_{r,p,\mathrm{mod}(n+\delta,p)}$ correspond to the values of pixels at radius r spaced δ elements apart. Function $\mathrm{mod}(x, y)$ is the modulus x of y.

Considering the rapid increase in the number of binary patterns as a function of the number of sampling points p, we don't want to derive local binary patterns directly from $\underline{\psi}^{\mathrm{Ang}}_{r,\delta,q}$, instead we transform the accumulated angular difference vector $\underline{\psi}^{\mathrm{Ang}}_{r,\delta,q}$ into a new vector $\underline{\phi}^{\mathrm{AngSign}}_{r,\delta,q}$ by local averaging along an arc,

$$\phi^{\mathrm{AngSign}}_{r,\delta,q,n} = \frac{1}{q}\sum_{k=0}^{q-1} \psi^{\mathrm{Ang}}_{r,\delta,q,(qn+k)}, \quad n = 0, \ldots, 7, \tag{6}$$

as illustrated in Fig. 2, such that the number of neighbors in $\underline{\phi}^{\mathrm{AngSign}}_{r,\delta,q}$ is always eight.

Given the sign component vector

$$\underline{\phi}^{\text{AngSign}}_{r,\delta,q} = [\phi^{\text{AngSign}}_{r,\delta,q,0}, \cdots, \phi^{\text{AngSign}}_{r,\delta,q,7}]^T, \tag{7}$$

we can trivially compute a binary pattern as in LBP_S:

$$\text{ADLBP\_S}_{r,\delta,q} = \sum_{n=0}^{7} s(\phi^{\text{AngSign}}_{r,\delta,q,n})2^n \tag{8}$$

where function $s(x)$ is defined in (1). One can easily see that for any parameter pair (r, q) there are $2^8 = 256$ patterns in total. Furthermore, the transformation from $\underline{\psi}^{\text{Ang}}_{r,\delta,q}$ to $\underline{\phi}^{\text{AngSign}}_{r,\delta,q}$ makes the pattern more robust to noise.

Similar to the LBP_M descriptor, we also propose ADLBP_M descriptor based on the magnitude of the angular differences $|\underline{\psi}^{\text{Ang}}_{r,\delta,q}|$. As before, we transform the absolute angular difference vector $|\underline{\psi}^{\text{Ang}}_{r,\delta,q}|$ into a new vector $\underline{\phi}^{\text{AngMag}}_{r,\delta,q}$ by locally averaging along an arc:

$$\phi^{\text{AngMag}}_{r,\delta,q,n} = \frac{1}{q}\sum_{k=0}^{q-1} |\psi^{\text{Ang}}_{r,\delta,q,(qn+k)}|, \quad n = 0, \ldots, 7. \tag{9}$$

Given $\underline{\phi}^{\text{AngMag}}_{r,\delta,q}$ we derive the ADLBP_M descriptor, as in LBP_M, via

$$\text{ADLBP\_M}_{r,\delta,q} = \sum_{n=0}^{7} s(\phi^{\text{AngMag}}_{r,\delta,q,n} - \mu^{\text{AngMag}}_{r,\delta,q})2^n, \tag{10}$$

where $\mu^{\text{AngMag}}_{r,\delta,q}$ is the average of $\{\phi^{\text{AngMag}}_{r,\delta,q,n}\}_{n=0}^{7}$.

2.3. Radial Differences-Based Descriptors

As a parallel development to the angular feature, we similarly define the radial differences-based descriptors RDLBP_S and RDLBP_M. We begin by computing the radial difference vector

$$\underline{\Delta}^{\text{Rad}}_{r,\delta,q} = [\Delta^{\text{Rad}}_{r,\delta,q,0}, \cdots, \Delta^{\text{Rad}}_{r,\delta,q,8q-1}]^T, \tag{11}$$

where

$$\Delta^{\text{Rad}}_{r,\delta,q,n} = x_{r,p,n} - x_{r-\delta,p,n} \tag{12}$$

is the radial difference computed with given integer radial displacement δ, $x_{r,p,n}$ and $x_{r-\delta,p,n}$ correspond to the gray values of δ equally spaced pixels of the same radial direction, as shown in the example of Fig. 2.

We can then compute the new transformed sign and magnitude components $\underline{\phi}^{\text{RadSign}}_{r,\delta,q}$ and $\underline{\phi}^{\text{RadMag}}_{r,\delta,q}$ vectors by the following:

$$\phi^{\text{RadSign}}_{r,\delta,q,n} = \frac{1}{q}\sum_{k=0}^{q-1} \Delta^{\text{Rad}}_{r,\delta,q,(qn+k)}, \quad n = 0, \ldots, 7 \tag{13}$$

$$\phi^{\text{RadMag}}_{r,\delta,q,n} = \frac{1}{q}\sum_{k=0}^{q-1} |\Delta^{\text{Rad}}_{r,\delta,q,(qn+k)}|, \quad n = 0, \ldots, 7. \tag{14}$$

Finally, similar to equations (8) and (10), the RDLBP_S and RDLBP_M descriptors are defined as

$$\text{RDLBP\_S}_{r,\delta,q} = \sum_{n=0}^{7} s(\phi^{\text{RadSign}}_{r,\delta,q,n})2^n \tag{15}$$

$$\text{RDLBP\_M}_{r,\delta,q} = \sum_{n=0}^{7} s(\phi^{\text{RadMag}}_{r,\delta,q,n} - \mu^{\text{RadMag}}_{r,\delta,q})2^n, \tag{16}$$

where $\mu^{\text{RadMag}}_{r,\delta,q}$ is the average of $\{\phi^{\text{RadMag}}_{r,\delta,q,n}\}_{n=0}^{7}$.

2.4. Face Recognition Pipeline

In standard face recognition tasks using LBP, only the uniform patterns are used [2, 5, 11]. The nonuniform patterns are considered in only a single bin of the histogram that is used to extract features in the classification stage. However, representing texture information using only the uniform patterns may be problematic, an issue which has also been raised by other researchers [12, 13], because the uniform patterns are not necessarily the dominant patterns, especially when the radius of LBP operator increases.

Indeed, in the case of our proposed six descriptors, we find that the property of the original uniform patterns [9] no longer hold true: We observe that the uniform patterns do not occupy the major pattern proportions, specifically in the case of the LBP_M, ADLBP_S, ADLBP_M and RDLBP_M descriptors. Consequently, textural information cannot be effectively represented by solely considering the histogram of the uniform patterns, and in this paper we propose to use the full descriptors, denoted as LBP_S$^{\text{full}}$, LBP_M$^{\text{full}}$ etc., meaning that there are 256 binary patterns for each descriptor at each scale.

The collection of the six LBP-like descriptors presented in Sections 2.1, 2.2 and 2.3 and illustrated in Fig. 2 we term as the Extended Local Binary Pattern (ELBP). Our face recognition pipeline is based on fusing all six ELBP descriptors (denoted as "ELBP_Fused"):

(1) An input face image is photometrically normalized by the preprocessing approach proposed by Tan and Triggs [14].

(2) The normalized face image is converted to six ELBP maps by applying the proposed ELBP feature extraction operators.

(3) Each ELBP map is further divided into $w \times w$ nonoverlapping regions and a subhistogram is computed for each region. The subhistograms are concatenated to form a single histogram feature. In this case, each face image is represented by six ELBP histogram features.

(4) In order to obtain a more discriminant and low-dimensional feature, we follow the recent work in [5, 7, 15] and apply the Whitened PCA (WPCA) dimensionality reduction technique to each ELBP histogram feature, leading to six lower dimensionality features denoted as $\underline{\boldsymbol{h}}_1, \cdots, \underline{\boldsymbol{h}}_6$.

(5) Classify a probe face with the identity of the nearest neighbor in the gallery. The Euclidean distance is used to measure two WPCA projected features and is denoted as $d(\underline{\boldsymbol{h}}_{ki}, \underline{\boldsymbol{h}}_{kj})$, where $\underline{\boldsymbol{h}}_{ki}$ and $\underline{\boldsymbol{h}}_{kj}$ are features computed from face image $\mathbf{I}_i$ and $\mathbf{I}_j$ respectively. For fusing the six ELBP features, we propose to use the sum of the similarity measures to measure the similarity of different face images $d(\mathbf{I}_i, \mathbf{I}_j) = \sum_{k=1}^{6} d(\underline{\boldsymbol{h}}_{ki}, \underline{\boldsymbol{h}}_{kj})$.

3. EXPERIMENTAL EVALUATION

3.1. Image Data and Experimental Setup

To evaluate the effectiveness of the proposed method, extensive experiments were carried out on two commonly used standard databases: Extended Yale B [16] and CAS-PEAL-R1 [17]. For each database we have used its standard evaluation protocol in order to facilitate comparisons with previous work.

The **Extended Yale B** database [16] consists of 2414 frontal face images of 38 subjects with each subject having about 64 samples, which were captured under laboratory controlled lighting conditions and were cropped and normalized to a standard size of 192×168 pixels. Instead of randomly selecting half of the images per subject for training and the rest for testing, we use a more difficult setup [18,19] in which the database was divided into five subsets according to the light direction with respect to the camera axis: subset 1 (S1) consisting of 263 images (7 images per subject) under nominal lighting conditions was used as the gallery, while all other subsets were used for probe. Subsets 2 and 3 consist of 456 and 525 images respectively, characterizing slight-to-moderate illumination variations, while subset 4 and subset 5 consist of 456 and 714 images respectively, depicting severe illumination changes.

The **CAS-PEAL-R1** database [17] is a large-scale Chinese face database for face recognition algorithm training and evaluation, containing 30,863 images of 1040 individuals. The gallery contains one image taken under standard conditions for each of the 1040 subjects. Here for probe sets, we use the expression, lighting, and accessory subsets, following the recent work of Lei *et al.* [7]. All of the images are cropped to a size of 150×130. CAS-PEAL-R1 is more difficult, both because it contains 27 times more subjects than Extended Yale B, and because it has a greater degree of intrinsic variability owing to its natural image capture conditions.

Implementation Parameters: For the LBP_S and LBP_M descriptors, we use a constant number of 8 sampling points for any radius r, consistent with other LBP face recognition work [2]. In terms of parameter q for the other four descriptors, we can set $q = r$, following the suggestion by Ojala *et al.* [9]. This arrangement may, however, cause over-smoothing at larger radii, so we apply a reasonable sampling scheme: $q = r$ for $r \leq 4$ and $q = 4$ for $r > 4$.

In terms of parameter δ, we have set $\delta = 1$ in all of our experiments. For the radius parameter r, we have tested $2 \leq r \leq 8$ and found $r = 4$ to be a good choice. The number of nonoverlapping subregions, $w \times w$, that a face image is partitioned into, we have set to $w = 9$, unless explicitly stated otherwise. The PCA dimension is selected as the number of images in the gallery set (1040 for the CAS-PEAL-R1); consistent with [5–7], WPCA is conducted on the gallery set only.

3.2. Results

Table 1 shows the recognition rates of the proposed single ELBP descriptors on the Extended Yale B database. Our results on this database are obtained with the elementary histogram features (without dimensionality reduction by WPCA), compared against recent state-of-the-art results in [18] and [19]. Based on Table 1 we can make the following observations. Firstly, for each proposed descriptor, the histogram representation generated by the full pattern method performs the best, significantly outperforming the uniform pattern method. The results clearly demonstrate the insufficiency of the uniform patterns for representing face images. Secondly, the magnitude-based descriptor outperforms the corresponding sign-based descriptor under very severe lighting changes (S4 and S5), indicating that using gradient magnitudes instead of the pixel intensity values for the construction of LBP-type descriptor can withstand severe luminance alterations. The good performance of the proposed elementary features clearly proves their strength for face recognition. Finally, the proposed LBP_S, LBP_M, ADLBP_M and RDLBP_M significantly outperform the state-of-the-art results obtained with a Linear Regression Classification (LRC) method under severe lighting variations.

Table 2 reports the results of the single ELBP descriptor and the ELBP_Fused approach, in comparison with state-of-the-art results on the CAS-PEAL-R1 database. Clearly, the ELBP_Fused approach consistently achieves much better recognition scores than any single ELBP descriptor, with an especially significant performance

Table 1. Recognition rates (%) of different methods on the Extended Yale B database. For our results, the NNC classifier with χ^2 distance measure is used.

Method	S2	S3	S4	S5	Mean
LBP_S^{u2}	99.8	99.6	93.2	77.7	92.6
LBP_M^{u2}	99.8	99.2	95.8	91.7	96.6
ADLBP_S^{u2}	99.8	89.5	28.5	12.5	57.6
ADLBP_M^{u2}	99.8	99.6	94.5	88.7	95.7
RDLBP_S^{u2}	99.8	99.4	91.9	68.5	89.9
RDLBP_M^{u2}	**99.8**	**99.6**	**98.2**	**91.5**	**97.3**
LBP_S^{full}	99.8	99.8	99.6	96.2	98.9
LBP_M^{full}	**99.8**	**99.6**	**99.6**	**97.6**	**99.2**
ADLBP_S^{full}	99.8	99.6	91.4	67.1	89.5
ADLBP_M^{full}	**99.8**	**99.6**	**99.4**	**97.8**	**99.2**
RDLBP_S^{full}	99.8	99.6	98.7	86.6	96.2
RDLBP_M^{full}	99.8	99.6	98.9	95.7	98.5
PCA [18]	98.5	80.0	15.8	24.4	54.7
LRC [18]	100	100	83.27	33.61	79.2
LRC_Fused [19]	100	100	88.97	84.73	93.4

Table 2. Recognition rates (%) of the proposed methods with state-of-the-art methods on the CAS-PEAL-R1 Database.

Method	Expression	Accessary	Lighting
LBP_S^{full}+WPCA	97.5	92.4	42.9
LBP_M^{full}+WPCA	94.1	85.1	36.5
ADLBP_S^{full}+WPCA	98.1	93.6	47.0
ADLBP_M^{full}+WPCA	95.1	87.0	42.1
RDLBP_S^{full}+WPCA	96.1	90.5	33.1
RDLBP_M^{full}+WPCA	91.3	78.1	34.8
ELBP_Fused	98.5	93.8	66.2
ELBP_Fused $(*)$	98.5	94.0	**72.3**
HGPP [4]	96.8	92.5	62.9
DT-LBP [20]	98.0	92.0	41.0
DLBP [21]	**99.0**	92.0	41.0
DFD+WPCA [7]	**99.0**	**96.9**	63.9

gain achieved for the CAS-PEAL-R1 Lighting probe set. The performance of the fused approach clearly indicates that the proposed descriptors do indeed capture different and complementary information. The performance of ELBP_Fused can be further improved by learning an optimal number of $w \times w$ subregions from the training set, given by ELBP_Fused $(*)$.

In comparison with state-of-the-art methods, the proposed ELBP_Fused method can achieve comparable results on the expression probe set. Regarding the accessory probe set, our ELBP_Fused method outperforms HGPP [4], which is known to be very computationally expensive, and the two learning based methods DT-LBP [20] and DLBP [21]. For the lighting probe set, our approach gives the highest recognition rate of 72.3%: This is 8% higher than the previous best result and is, to the best of our knowledge, the best score ever achieved on this data set, indicating the strength of our approach in relation to previous learning based methods.

4. CONCLUSIONS

In this paper we have proposed a novel extended set of LBP-like descriptors and have developed a very simple framework to fuse the proposed descriptors for the problem of face identification. Our main findings are as follows: (i) The proposed ELBP descriptors exploit most of the information available locally and do contain complementary information with each other, which is evidenced by the improved performance obtained by fused descriptors; (ii) The traditional uniform patterns approach does not apply to the proposed descriptors, instead we find that full patterns give good recognition performance; (iii) The WPCA technique can further improve the recognition performance of the fused proposed features.

Extensive experiments on Extended Yale B and CAS-PEAL-R1 databases have shown that the proposed approach can give comparable or much improved results compared to state-of-the-art methods.

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