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Face Recognition under Varying Lighting Conditions: A Combination of Weber-face and Local Directional Pattern for Feature Extraction and Support Vector Machines for Classification

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Abstract. *In the last two decades, an increasing number of illumination pretreatment methods and local feature descriptors have been proposed to address the issue of face recognition under different illumination conditions. Although these have achieved impressive results, the problem of how to maximize the reduction of the effect of variable lighting on captured images remains open. We assume that face images for training are captured under good lighting environments, and face images for testing are captured under various lighting environments, and propose a new approach as follows: (i) normalize the illumination components of face images using the Weber–face method; (ii) extract the features of the obtained images using a local directional pattern descriptor; and (iii) use support vector machines (SVM) for classification. The potential of the proposed approach is demonstrated by comparing a combination of illumination normalization methods (histogram equalization, Gradientfaces, and Weber–face), local descriptors (center–symmetric local binary pattern, local binary pattern, local phase quantization, local ternary pattern, and rotated local binary pattern) and the PCA method using nearest–neighbor and SVM classifiers. Experimental results for the extended Yale B face database indicate that the proposed approach achieves an accuracy of 0.12% to 4.26% higher than other methods using the same approach.*
Keywords: Face recognition, Illumination pretreatment, Weber–face, Local directional pattern, Support vector machines.

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1. **Introduction.** Face recognition plays an important role in the area of biometric identification, and is used in many applications such as identity authentication, access control and surveillance [1]. There are many factors which affect the identification accuracy of a face recognition system, such as variations in illumination, changes in pose, facial expressions, variations in age and occlusion. Of these, variation in illumination is considered to be one of the most significant problems, since the appearance of a face in a captured

image can be greatly altered [2]. Within the past twenty years, numerous strategies have been employed to overcome this issue. They can be categorized into two main types: illumination normalization methods and feature extractors.

Illumination normalization methods are applied to process the illumination components of a face image; the output of these methods is still an image. Gradientfaces (GF) [3] and Weber–face (WF) [4] are two well–known illumination normalization methods which obtain good results for facial recognition under various lighting conditions. The GF method is a gradient–based preprocessing technique which assumes that the illumination components of a face image change slowly. It finds an illumination–insensitive representation using the ratio of directional gradients. In the WF method, the illumination–insensitive image is calculated using Weber's law, which assumes that the ratio between the smallest perceptual change in a stimulus, and the background level of the stimulus is a constant. In [4], it was shown that the WF method obtained a better result compared to the GF method in illumination effect suppression.

Feature extractors can be separated into the two major types of holistic–based and local-based techniques. Many holistic methods, such as principal component analysis (PCA) [5] and linear discriminant analysis (LDA) [6], have been proved successful in face recognition. However, local–based methods suffer much less from local appearance changes than holistic–based methods [7]. Numerous local–based methods have been proposed, such as local binary pattern (LBP) [8, 9], local directional pattern (LDP) [10, 11, 12], local ternary pattern (LTP) [9, 13], and local phase quantization (LPQ) [14]. Of these, LBP and LTP have been proved effective in face recognition under monotonic illumination changes [8, 13, 15]. LPQ is known to be an illumination– and blur–insensitive feature extractor [16, 17, 18]. In [11], it was shown that the LDP descriptor is robust to lighting conditions and aging effects in comparison with the LBP descriptor. In [19], authors introduced an approach using LDP images and the 2D–PCA algorithm to improve face recognition accuracy under illumination–variant environments.

As mentioned above, the output of an illumination suppression method is still an image, and it is therefore necessary to use descriptors to extract the features of the normalized images. If this combination is suitable, it will increase the performance of a face recognition system.

In fact, training face images are often captured in good, stable lighting environments, while testing face images are captured in varying lighting environments. In view of this, we propose an approach for face recognition under varying illumination conditions as follows: (i) normalize the illumination components of face images using the WF method; (ii) extract the features of the obtained images using LDP; and (iii) use support vector machines (SVM) [20] for classification. Two face recognition systems are developed; the first is based on the nearest neighbor classifier, the second on the SVM classifier. The effect of the proposed approach is demonstrated through a comparison with other methods, which include the illumination preprocessing methods (histogram equalization [21], GF, and WF), local descriptors (center–symmetric local binary pattern (CS–LBP) [22], LBP, LPQ, rotated local binary pattern (RLBP) [23], and LTP) and the PCA method, using the extended Yale B face database [24].

The remainder of this paper is structured as follows: Section 2 gives a brief overview of related work; Section 3 introduces the face recognition protocol and our approach; the results of experimental testing of this method are presented and a discussion offered in Section 4; and Section 5 concludes this work.

2. **Related works.**

2.1. The Weber–face method.

2.1.1. *Weber's law.* Weber′s law was first introduced by Ernst Weber, and states that the ratio between the smallest perceptual change in a stimulus (ΔI) and background level of the stimulus (I) is a constant. This means that

$$\frac{\Delta I}{I} = k, \tag{1}$$

where k is the Weber fraction. Weber′s law implies that the above formula remains a constant despite variations in the I term.

2.1.2. *Weber–face.* The Weber–face (WF) method [4] was proposed for an illumination–insensitive representation of a face image based on Weber′s law. The implementation of this approach consists of two steps, as follows:

Step 1. Smooth F using a Gaussian filter:

$$F' = F * G(x, y, \sigma), \tag{2}$$

where * is the convolution operator and G is the Gaussian kernel function with standard deviation σ.

Step 2. Process F' with a Weber local descriptor:

$$WF = WLD(F'), \tag{3}$$

where WLD(•) is a Weber local descriptor:

$$WLD(F'(x,y)) = \arctan(\alpha \sum_{i \in A} \sum_{j \in A} \frac{F'(x,y) - F'(x - i\Delta x, y - j\Delta y)}{F'(x,y)}), \tag{4}$$

where A=(-1,0 or 1) and *f(x,y)* is the intensity value of the pixel at location *(x,y)*. The arctangent function is a normalization function and the parameter is a weight coefficient for adjusting the relativity between the intensity difference and current central pixel.

2.2. Local directional pattern.

The local directional pattern [10, 12], which is a local gray–scale texture pattern, assigns to each pixel of an input image an eight–bit binary code. A LDP operator computes the edge response values in all eight directions at each pixel position and generates a binary code from the relative strength magnitude. An LDP operator consists of three steps, as follows:

Step 1. Given a central pixel of a 3 × 3 neighborhood in the image, and applying Kirsch masks, we obtain eight edge response values, $m_0, m_1, \ldots, m_7$. These Kirsch masks are shown in Figure 1.

Step 2. Find the top k values $\mid m_i \mid$and set them to 1. The remaining (8-k) bits of the eight–bit LDP pattern are set to 0. Figure 2 shows the eight directional edge response positions and LDP binary bit positions.

Step 3. The LDP code is derived, which is calculated as follows:

$$LDP_k = \sum_{i=0}^{7} s(m_i - m_k) 2^i, \tag{5}$$

where m_k is the k−th most significant directional response and the step function $s(x)$ is defined as Equation(6). Figure 3 displays three steps of an example of LDP code with k=3.

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}. \tag{6}$$

$$\underset{\text{East }(M_0)}{\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}} \quad \underset{\text{North East }(M_1)}{\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}} \quad \underset{\text{North }(M_2)}{\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}} \quad \underset{\text{North West }(M_3)}{\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}}$$

$$\underset{\text{West }(M_4)}{\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}} \quad \underset{\text{South West }(M_5)}{\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}} \quad \underset{\text{South }(M_6)}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix}} \quad \underset{\text{South East }(M_7)}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}}$$

FIGURE 1. Kirsch edge response masks in eight directions.

m_3	m_2	m_1
m_4	X	m_0
m_5	m_6	m_7

b_3	b_2	b_1
b_4	X	b_0
b_5	b_6	b_7

FIGURE 2. Edge response and LDP binary bit positions.

7	5	3
6	6	1
9	4	2

Mask index	m_7	m_6	m_5	m_4	m_3	m_2	m_1	m_0
Mask value	55	9	41	65	33	9	39	63
Rank	3	8	4	1	6	7	5	2
Code bit	1	0	0	1	0	0	0	1
LDP code	145							

FIGURE 3. Generating LDP code with k=3.

2.3. **Support vector machines classifier.** Support vector machines (SVM) were proposed by Vapnik (1995) [20], and form the basis of a binary classifier that has proven effective in pattern classification. The goal of SVM is to find a hyperplane that separates the data points of two different classes. In practice, there may be multiple possible hyperplane separators between the two classes. However, the classifier seeks the optimal separating hyperplane which maximizes the margin of the data points (Figure 4). For details of the SVM approach, the reader is referred to [25, 26].

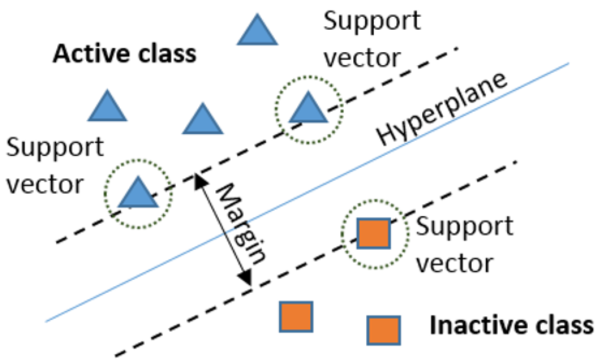

FIGURE 4. Maximum–margin hyperplane and margins for an SVM trained with samples from two classes.

3. Feature extraction protocol and the proposed approach.

3.1. **Feature extraction protocol.** Firstly, the face images, either with or without illumination normalization, are encoded by local descriptors. Next, in order to improve the effectiveness of the descriptors, an encoded image is divided into a set of small sub–regions from which histograms are extracted and concatenated into a single feature histogram. Suppose a sub–region of the given image is of size I*J. A histogram is constructed to represent a sub–region of the encoded image as follows:

$$H(k) = \sum_{i=1}^{I}\sum_{j=1}^{J} f(LD_{R,P}(i,j),k), k \in [0,K], f(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases}. \tag{7}$$

where K is the maximal pattern value and LD are local descriptors. For details of this approach, the reader may refer to [9, 27].

3.2. **Proposed approach.** In this study, we preprocess the face image using the WF method. The output of this step is still a face image, and thus the LDP descriptor is applied after illumination preprocessing. The classification is performed using an SVM classifier. Figure 5 presents the general diagram of the proposed approach.

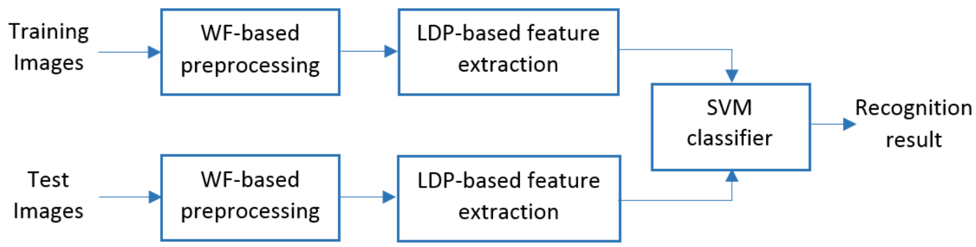

FIGURE 5. Block diagram of the proposed recognition system.

4. Experimental results and discussion.

4.1. **Experiment setting.** Matlab version R2014b was used in this study, and where possible, the available functions of Matlab were used. In order to evaluate the performance of the proposed approach, two face recognition systems were developed; the first was based on the nearest–neighbor classifier, and the second on the SVM classifier. The Chi–square distance was used in the first system, while the *fitcecoc* function with SVM models using the one versus all encoding scheme was used in the second system. For the methods using PCA, the L_2 metric was used as a measure of distance. For the HE method, the number of discrete gray levels was set to 64. For the WF method, the number of neighbors was eight, the parameter σ was set to 1, the parameter α was set to 2, and the output result was normalized to the eight–bit interval. For the CSLBP method, the value of threshold t was chosen as 0. For the LDP method, the parameter k was chosen as 3. For the LTP method, the value of threshold t was chosen as 1.

The accuracy of each method was calculated as the percentage of correct classifications, which is computed as follows:

$$\text{Accuracy}(\%) = \frac{\#\text{of correct classifications}}{\#\text{of total testing images}} \times 100. \tag{8}$$

4.2. **Results on extended Yale B.** The extended Yale B face database [24] is widely used in testing proposed methods for face recognition under different lighting conditions. It contains gray–scale frontal face images of size 192×168 pixels for 38 individuals in 9 poses and with 64 illumination conditions per pose. Each subject has 64 images (2414 images out of 2432 images are used, since 18 images are either missing or labeled as bad by the owners). The images are categorized into six subsets, based on the angle between the direction of the light source and the central camera axis, as follows: Subset 0 (0°, 228 images), Subset 1 (1°–12°, 301 images), Subset 2 (13°–25°, 380 images), Subset 3 (26°–50°, 449 images), Subset 4 (51°–77°, 380 images), and Subset 5 (above 77°, 676 images). We conducted experiments on this database and used Subset 0 (A+000E+00), captured under natural illumination conditions, for training. The remaining subsets were used for testing. In the experiments, each image was divided into 10×10 blocks. The original sample images, the images represented by WF, and the images encoded by LDP are shown in Figure 6.

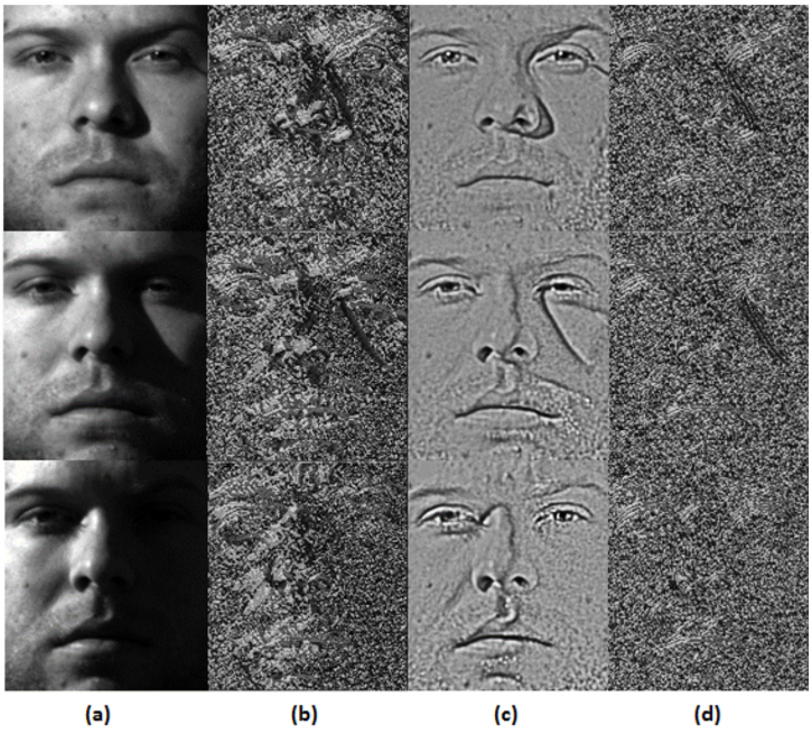

Figure 6. The original sample images and the corresponding images of the extended Yale B database: (a) original images; (b) LDP–based images; (c) WF–based images; (d) images using WF followed by LDP.

The experimental results of the normalization methods combined with the PCA method are displayed in Table 1. The mean accuracies of GF, HE, and WF and PCA were 91.34%, 50.70% and 98.44% respectively. It was found that WF + PCA achieved the highest result, while HE + PCA obtained the lowest result.

Table 1. Percentage accuracy of principal component analysis method

Methods	S1	S2	S3	S4	S5	Average
GF + PCA	99.66	99.47	91.53	82.63	83.43	91.34
HE + PCA	99.33	81.31	28.95	14.21	29.73	50.70
WF + PCA	99.33	100	98.21	97.63	97.04	**98.44**

Tables 2 and 3 show the percentage accuracy of recognition of the descriptors and the normalization methods followed by the descriptors, with nearest–neighbor and SVM classifiers respectively. In Table 2, the first six rows are the results of local descriptors without illumination normalization, and the remaining rows are the results of the combined methods using both normalization methods and local descriptors. A similar format is used in Table 3.

Table 2. Percentage accuracy of local descriptor methods using nearest neighbor classifier

Methods	S1	S2	S3	S4	S5	Average
CSLBP + NN	100	99.47	94.65	54.21	50.88	79.84
LBP + NN	100	99.47	95.10	51.31	46.74	78.52
LDP + NN	100	99.47	92.42	36.84	38.60	73.47
LPQ + NN	100	99.47	94.43	74.73	63.46	**86.42**
LTP + NN	100	99.47	95.10	55.26	50.00	79.96
RLBP + NN	100	99.47	79.06	25.00	21.44	64.99
GF + CSLBP + NN	100	99.47	94.43	56.84	48.07	79.76
GF + LBP + NN	100	99.47	97.10	78.68	59.17	86.88
GF + LDP + NN	100	99.47	95.10	60.00	53.99	81.71
GF + LPQ + NN	100	99.47	96.65	71.31	62.13	85.91
GF + LTP + NN	100	99.47	97.32	81.84	60.35	**87.79**
GF + RLBP + NN	100	99.47	89.75	41.31	43.93	74.89
HE + CSLBP + NN	100	99.47	93.54	45.78	53.55	78.47
HE + LBP + NN	100	99.47	92.87	53.42	61.39	81.43
HE + LDP + NN	100	99.47	87.08	40.52	49.55	75.32
HE + LPQ + NN	100	99.73	93.98	56.05	53.84	80.72
HE + LTP + NN	100	99.47	93.31	53.94	61.24	**81.59**
HE + RLBP + NN	100	99.21	67.03	24.73	37.57	65.71
WF + CSLBP + NN	100	99.73	98.21	84.73	65.23	89.58
WF + LBP + NN	100	99.47	98.88	95.52	73.96	93.57
WF + LDP + NN	100	100	98.21	87.89	72.18	91.66
WF + LPQ + NN	100	99.73	98.66	96.57	81.80	**95.35**
WF + LTP + NN	100	99.47	98.44	96.05	75.59	93.91
WF + RLBP + NN	100	99.47	90.20	75.26	53.10	83.60

Abbreviations: Si: Subset; GF: Gradientfaces method; HE: histogram equalization method; WF: Weber–face method; CSLBP: center–symmetric local binary pattern; LBP: local binary pattern; LDP: local directional pattern; LPQ: local phase quantization; LTP: local ternary pattern; RLBP: rotated local binary pattern; NN: nearest neighbor classifier.

As shown in the first six rows of Table 2, the LPQ average recognition rate was 86.42%, which was 6.58%, 7.9%, 12.95%, 6.49%, and 21.43% higher than that of CSLBP, LBP, LDP, LTP, and RLBP respectively. The second six rows show that the average recognition rate of GF with LTP was 87.79%, which was 8.03%, 0.91%, 6.08%, 1.88%, and 12.9% higher than that of CSLBP, LBP, LDP, LPQ, and RLBP respectively. The third six rows show that HE combined with LTP reached the highest average recognition rate of 81.59%, which was 3.12%, 0.16%, 6.27%, 0.87%, and 15.88% higher than that of CSLBP, LBP, LDP, LPQ, and RLBP respectively. The last six rows show that the WF + LPQ average recognition rate was 95.35%, which was 5.77%, 1.78%, 3.69%, 1.44% and 11.75% higher than that of WF + CSLBP, WF + LBP, WF + LDP, WF + LTP, and WF + RLBP, respectively. It can be seen that a combination of WF and the descriptors showed average recognition rates higher than those of the other methods, both with and without illumination treatment methods.

Table 3. Percentage accuracy of local descriptor methods using support vector machine classifier

Methods	S1	S2	S3	S4	S5	Average
CSLBP + SVM	100	99.47	94.87	71.84	61.53	85.54
LBP + SVM	100	99.47	91.53	50.52	40.68	76.44
LDP + SVM	100	99.47	95.99	85.00	79.14	91.92
LPQ + SVM	100	99.47	98.88	93.42	80.76	**94.51**
LTP + SVM	100	99.47	93.76	55.52	43.04	78.36
RLBP + SVM	100	99.47	84.63	41.84	36.24	72.43
GF + CSLBP + SVM	100	99.47	99.10	95.52	84.91	**95.80**
GF + LBP + SVM	100	99.73	99.33	97.10	79.29	95.09
GF + LDP + SVM	100	99.47	99.10	95.00	79.73	94.66
GF + LPQ + SVM	100	99.73	98.21	96.05	56.50	90.10
GF + LTP + SVM	100	99.47	98.88	91.31	78.99	93.73
GF + RLBP + SVM	100	99.47	90.64	63.15	47.18	80.09
HE + CSLBP + SVM	100	99.47	93.76	63.68	58.87	83.15
HE + LBP + SVM	100	99.47	91.75	67.63	60.65	83.90
HE + LDP + SVM	100	99.47	93.31	76.05	72.48	**88.26**
HE + LPQ + SVM	100	98.68	88.64	58.94	46.30	78.51
HE + LTP + SVM	100	99.47	94.43	70.26	60.79	84.99
HE + RLBP + SVM	100	96.84	72.16	42.63	47.18	71.76
WF + CSLBP + SVM	100	99.73	99.55	99.21	96.74	99.04
WF + LBP + SVM	100	99.47	99.33	99.21	95.56	98.71
WF + LDP + SVM	100	99.73	99.55	99.73	97.04	**99.21**
WF + LPQ + SVM	100	99.73	99.33	99.21	97.18	99.09
WF + LTP + SVM	100	99.47	99.10	99.21	94.67	98.49
WF + RLBP + SVM	100	99.47	98.44	94.73	82.10	94.95

Abbreviations: Si: Subset; GF: Gradientfaces method; HE: histogram equalization method; WF: Weber–face method; CSLBP: center–symmetric local binary pattern; LBP: local binary pattern; LDP: local directional pattern; LPQ: local phase quantization; LTP: local ternary pattern; RLBP: rotated local binary pattern; SVM: support vector machines classifier.

As shown in the first six rows of Table 3, the average recognition rate of LPQ was 94.51%, which was 8.97%, 18.07%, 2.59%, 16.15%, and 22.08% higher than that of CSLBP, LBP, LDP, LTP, and RLBP respectively. The findings also showed that the LDP average recognition accuracy was 91.92%, which was 6.38%, 15.48%, 13.56%, and 19.49% higher than that of the CSLBP, LBP, LTP, and RLBP methods respectively. This suggests that LDP with SVM also obtains a good result for face recognition under different lighting conditions. The second six rows show that the CSLBP method achieved the highest average recognition rate of 95.8%, which was 0.71%, 1.14%, 5.7%, 2.07%, and 15.71% higher than that of LBP, LDP, LPQ, LTP, and RLBP respectively. The third six rows show that the LDP method reached 88.26%, while the mean accuracies were 83.15%, 83.90%, 78.51%, 84.99%, and 71.76% for CSLBP, LBP, LPQ, LTP, and RLBP respectively. The last six rows show that the proposed method achieved the highest average recognition rate of 99.21%, which was 0.17%, 0.5%, 0.12%, 0.72%, and 4.26% higher than that of CSLBP, LBP, LPQ, LTP, and RLBP respectively.

The results in Tables $1 \div 3$ indicate that the obtained average rates for SVM are higher than that for NN since the training images, which were captured under good lighting conditions with or without using illumination methods, can help SVM in finding a better hyperplane that separates the features of the two different classes more easily. These results also confirm that WF enables a reduction in information inaccuracy after illumination suppression and preserves more characteristic information for recognition than GF and HE. In addition, it can be observed that the combination of WF and local descriptors for feature extraction and SVM for classification outperforms the other methods, which use local descriptors and PCA, with or without illumination normalization methods, for feature extraction and the NN and SVM classifiers for classification. Of the highest accuracies obtained, our method achieved a higher mean recognition accuracy than the related methods of 0.12% to 4.26%.

Table 4. Percentage accuracy of local descriptor methods using support vector machine classifier

Methods	Average
PCA [19]	30.03
2D-PCA [19]	30.78
LBP + PCA [19]	72.09
LBP + 2D-PCA [19]	91.54
Gabor-wavelets + LBP [19]	69.50
LDP + PCA [19]	81.34
LDP + 2D-PCA [19]	96.43
Proposed method	**99.21**

Abbreviations: 2D–PCA: two–dimensional principal component analysis.

Table 4 gives the results reported in [19] and the average accuracy of the proposed method. In [19], the authors used the LDP descriptor to encode the face images and the 2D–PCA algorithm to extract the features of the LDP images. The mean recognition accuracy of this method was 96.43%, which was 15.09% higher than that of the LDP + PCA method. However, this result was still 2.78% lower than that of our method. From the analysis above, it can be seen that the approach proposed here is a very effective method, and this is expected to contribute further to existing strategies in face recognition under changing lighting conditions.

5. **Conclusion.** In this paper, we introduce a technique for face recognition under various lighting conditions, in which the Weber–face method is used to normalize illumination, local directional pattern (LDP) is applied to extract the features, and support vector machines (SVM) are used for classification. Two face recognition systems are developed, the first of which is based on the nearest–neighbor classifier, and the second on the SVM classifier. Both of these systems use histogram equalization, Gradientfaces and Weber–face methods to normalize the illumination of the face images and extract the features of normalized images using center–symmetric local binary pattern, local binary pattern, local directional pattern, local phase quantization, rotated local binary pattern, and local ternary pattern descriptors. Experiments were conducted on the extended Yale B face database, and these indicated that the proposed approach achieved a recognition accuracy that is $0.12\% \div 4.26\%$ better than other methods using the same approach. This is due to the ability of the SVM classifier to find a good hyperplane when the features of an image captured under natural lighting are extracted using the Weber–face method followed by the LDP descriptor. The proposed approach is expected to contribute further to existing strategies for face recognition under changing lighting conditions.

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http://www.ee.oulu.fi/mvg/page/lbp_matlab;
http://parnec.nuaa.edu.cn/xtan/Publication.htm;
http://www.cse.oulu.fi/CMV/Downloads/LPQMatlab;
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