Face Recognition via Local Directional Pattern

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Abstract

In this paper, we propose an illumination-robust face recognition system via local directional pattern images. Usually, local pattern descriptors including local binary pattern and local directional pattern have been used in the field of the face recognition and facial expression recognition, since local pattern descriptors have important properties to be robust against the illumination changes and computational simplicity. Thus, this paper represents the face recognition approach that employs the local directional pattern descriptor and two-dimensional principal analysis algorithms to achieve enhanced recognition accuracy. In particular, we propose a novel methodology that utilizes the transformed image obtained from local directional pattern descriptor as the direct input image of two-dimensional principal analysis algorithms, unlike that most of previous works employed the local pattern descriptors to acquire the histogram features. The performance evaluation of proposed system was performed using well-known approaches such as principal component analysis and Gabor-wavelets based on local binary pattern, and publicly available databases including the Yale B database and the CMU-PIE database were employed. Through experimental results, the proposed system showed the best recognition accuracy compared to different approaches, and we confirmed the effectiveness of the proposed method under varying lighting conditions.

Keywords: *Face Recognition, Local Directional Pattern*

1. Introduction

Recently, face recognition has become one of the most popular research areas in the fields of image processing, pattern recognition, computer vision, and machine learning, because it spans numerous applications [1, 2]. Face recognition has many applications such as biometrics systems, access control systems, surveillance systems, security systems, credit-card verification systems, and content-based video retrieval systems. Up to now, main algorithms have been applied to describe the faces: principal component analysis (PCA) [3, 4], linear discriminant analysis (LDA) [5, 6], independent component analysis (ICA) [7], two-dimensional principal component analysis (2D-PCA) [8], elastic bunch graph matching (EBGM) [9], artificial neural networks [10], embedded hidden Markov models (EHMM) [11], Gabor wavelets [12], and so on. Generally, face recognition systems can achieve good performance under controlled environments. However, face recognition systems tend to suffer when variations in different factors such as varying illuminations, poses, expression are present, and occlusion. In particular, illumination variation that occurs on face images drastically degrades the recognition accuracy.

To overcome the problem caused by illumination variation, various approaches have been introduced, such as preprocessing and illumination normalization techniques [13, 14], illumination invariant feature extraction techniques [15, 16], and 3D face modeling techniques [17, 18]. Among abovementioned approaches, local binary pattern (LBP) [14] has received increasing interest for face representation in general [19, 20]. LBP was originally proposed for texture description [21], and has been widely exploited in many applications such as video retrieval, aerial image analysis, and visual inspection. Recently, LBP have been extensively exploited for facial image analysis, including face detection, face recognition, facial expression analysis, gender/age classification, and so on [22, 23]. The LBP is a non-parametric kernel which summarizes the local spatial structure of an image. Moreover, it has important properties to be tolerant against the monotonic illumination changes and computational simplicity. More recently, the local directional pattern (LDP) method was introduced by Jabid et. al for a more robust facial representation [24, 25]. Because LBP is sensitive to non-monotonic illumination variation and also shows poor performance in the presence of random noise, they proposed the LDP descriptor as face representation and also demonstrated better performance compared to LBP.

In this paper, we present a novel approach for achieving the illumination invariant face recognition via LDP image. Most of previous face recognition researches based on LBP utilized the descriptor for histogram feature extraction of the face image. Similar to LBP, LDP descriptor is also utilized to extract the histogram facial features in previous researches [24, 25]. However, this paper uses the LDP image as a direct input image of 2D-PCA algorithms for illumination-robust face recognition system. The proposed approach has an advantage that the illumination effects can be degraded by using binary pattern descriptor and 2D-PCA is more robust against illumination variation than global features such as PCA and LDA since 2D-PCA is a line-based local feature. The performance evaluation of the proposed system was carried out using the Yale B database [26] and the CMU-PIE illumination/light database [27]. Consequently, we will demonstrate the effectiveness of the proposed approach by comparing our experimental results to those obtained with other approaches.

2. Proposed Approach

This paper aimed to improve face recognition accuracy under illumination-variant environments by using the LDP image and 2D-PCA algorithm. The LDP image is derived from the edge response values in different eight directions Next, the LDP image is directly inputted in 2D-PCA algorithm and nearest neighbor classifier is applied to recognize unknown user. Remark that the proposed face recognition system is very different approach when compared to previous works, because most of previous works were used the local pattern descriptors to extract the histogram features. However, we utilize the transformed image from local pattern descriptor, i.e. LDP image as input image for further feature extraction procedure, i.e. 2D-PCA algorithm. The advantage of the proposed approach is that the illumination effects on face can be degraded by using binary pattern descriptor, and also 2D-PCA is more robust against illumination variation than global features such as PCA and LDA since 2D-PCA is a line-based local feature. In fact, we will be show that the recognition accuracy of the proposed system outperforms that of conventional approaches in the experimental results.

2.1. Local Directional Pattern

The LBP operator labels the pixels of an image by thresholding a 3x3 neighborhood of each pixel with the center value and considering the results as a binary number, of which the corresponding decimal number is used for labeling. The derived binary numbers are called local binary patterns or LBP codes. While the LBP operator uses the information of intensity changes around pixels, LDP operator use the edge response values of neighborhood pixels and encode the image texture. The LDP is computed as follow [24, 25]. The LDP assigns an 8 bit binary code to each pixel of an input image. This pattern is then calculated by comparing the relative edge response values of a pixel by using Kirsch edge detector. Given a central pixel in the image, the eight-directional edge response values $m_i\ (i = 0, 1, \cdots, 7)$ are computed by Kirsch masks as shown in Figure 1. Since the presence of a corner or an edge shows high response values in some particular directions, thus, most prominent directions of k number with high response values are selected to generate the LDP code. In other words, *top-k* directional bit responses, b_i , are set to 1, and the remaining $(8-k)$ bits are set to 0. Finally, the LDP code is derived by

$$LDP_k = \sum_{i=0}^{7} b_i(m_i - m_k) \times 2^i , \quad b_i(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}, \tag{1}$$

where m_k is the k-th most significant directional response. Figure 2 shows an example of LDP code with $k = 3$.

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 1. Edge Response and LDP Binary Bit Positions

85	32	26
53	50	10
60	38	45

→

313	97	503
537	X	399
161	97	303

→

0	0	1
1	X	1
0	0	0

LDP binary code : 00010011
LDP decimal code : 19

Figure 2. LDP Code with $k = 3$

2.2. Two-dimensional Principal Component Analysis

Principal component analysis is a well-known feature extraction and data representation technique widely used in the areas of pattern recognition, computer vision, signal processing, and so on. The central underlying concept is to reduce the dimensionality of a data set while retaining the variations in the data set as much as possible [3, 4]. In the PCA-based face recognition method, 2D face image matrices must be previously transformed into 1D image vectors column by column or row by row fashions. However, concatenating 2D matrices into 1D vector often leads to a high-dimensional vector space, where it is difficult to evaluate the covariance matrix accurately due to its large size. Furthermore, computing the eigenvectors of a large covariance matrix is very time-consuming [8].

To overcome these problems, a new technique called 2D-PCA was proposed, which directly computes eigenvectors of the so-called image covariance matrix without matrix-to-vector conversion. Because the size of the image covariance matrix is equal to the width of images, which is quite small compared with the size of a covariance matrix in PCA, 2D-PCA evaluates the image covariance matrix more accurately and computes the corresponding eigenvectors more efficiently than PCA. It was reported that the recognition accuracy of 2D-PCA on several face databases was higher than that of PCA, and the feature extraction method of 2D-PCA is computationally more efficient than PCA. Unlike PCA, which treats 2D images as 1D image vectors, 2D-PCA views an image as a matrix. Consider an m by n image matrix A. Let $X \in R^{n \times d}$ be a matrix with orthonormal columns, $n \geq d$. Projecting A onto X yields m by d matrix $Y = AX$. In 2D-PCA, the total scatter of the projected samples is used to determine a good projection matrix X. Suppose that there are M training face images, denoted m by n matrices A_k $(k = 1, 2, \cdots, M)$, and the average image is denoted as $\overline{A} = 1/M \sum_k A_k$.

Then, the image covariance matrix, G is given by

$$G = \frac{1}{M} \sum_{k=1}^{M} (A_k - \overline{A})^T (A_k - \overline{A}). \tag{2}$$

It has been proven that the optimal value for the projection matrix X_{opt} is composed by the orthonormal eigenvectors $X_1, X_2, \cdots, X_d$ of G corresponding to the d largest eigenvalues, i.e., $X_{opt} = [X_1, X_2, \cdots, X_d]$. Since the size of G is only n by n, computing its eigenvectors is very efficient. The optimal projection vectors of 2D-PCA, $X_1, X_2, \cdots, X_d$ are used for feature extraction. For a given face image A, the feature vector $Y = [Y_1, Y_2, \cdots, Y_d]$, in which Y has a dimension of m by d, is obtained by projecting the images into the eigenvectors as follows:

$$Y_k = (A - \overline{A}) X_k, \quad k = 1, 2, \cdots d. \tag{3}$$

After feature extraction by 2D-PCA, the Euclidean distance is used to measure the similarity between the training and test features. Suppose that each training image A_k is projected onto X_{opt} to obtain the respective 2D-PCA feature F^k. Also, let A be a given image for testing and its 2D-PCA feature be F. Then, the Euclidean distance between F and F^k is computed by

$$d(F, F^k) = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{d} (f_{i,j}^k - f_{i,j})^2}, \tag{4}$$

where k is $1, 2, \cdots, M$, and M is the total number of training images. This distance measurement between 2D-PCA features is further employed to classify unknown user.

3. Experimental Results

To evaluate the robustness of the proposed method, we used images from the Yale B database [26] and CMU-PIE database [27]. In the Yale B database, we employ 2,414 face images for 38 subjects representing 64 illumination conditions under the frontal pose, in which subjects comprised 10 individuals in the original Yale face database B and 28 individuals in the extended Yale B database. The CMU-PIE database contains more than 40,000 facial images of 68 individuals, 21 illumination conditions, 22 light conditions, 13 poses and four different expressions. Among them, we selected each illumination and light images of 68 individuals with frontal pose (c27). So, the CMU-PIE illumination set consists of 21 images of 68 individuals (21×68 images in total), and the CMU-PIE illumination set also consists of 22 images of 68 individuals (22×68 images in total). All face images of two databases were converted as grayscale and were cropped and normalized to a resolution of 48×42 pixels. Figure 3 show an example of raw, histogram equalization, LBP, and LDP images in CMU-PIE illumination database, respectively. Remark that LDP images are divided into different groups as k number. The performance evaluation was carried out using each database of the Yale B database and CMU-PIE illumination/light database with each pre-processing images.

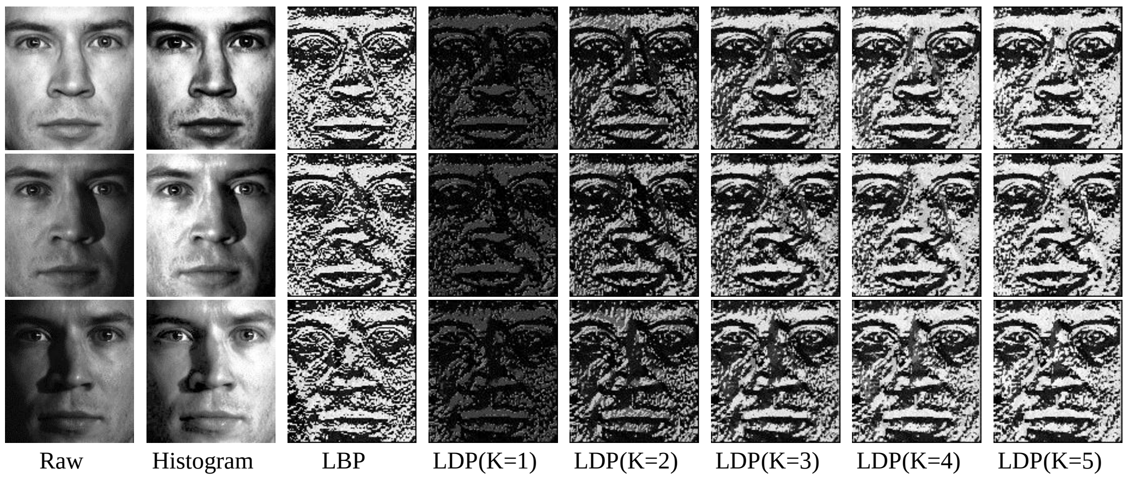

Figure 3. Input Images for CMU-PIE Illumination Database

3.1. Yale B Database

To evaluate the performance of the proposed method, we partitioned the Yale B database into training and testing sets. Each training set comprised of seven images per subject, and the remaining images were used to test the proposed method. We selected the illumination-invariant images for training, and the remaining images with varying illumination were employed for testing. Next, we investigated the recognition performance of proposed approach with conventional recognition algorithms such as PCA and Gabor-wavelet based on LBP. For the Yale B database, the recognition results in terms of different pre-processing images and algorithms are shown in Figure 4. To further disclose the relationship between the recognition rate and dimensions of feature vectors, we showed the recognition results along with different dimensions in Figure 4. Also, we summarized the maximum recognition rates as various approaches in Table 1. As a result, the proposed approach using LDP and 2D-PCA showed a maximum recognition rate of 96.43%, when k is 3. However, the maximum recognition rates revealed 81.34% and 69.50% for PCA and Gabor-wavelets based on LBP approaches, respectively. Consequently, the recognition accuracy of proposed method was better than that of conventional methods, and it also shows performance improvement ranging from 15.09% to 29.63% in comparison to conventional methods.

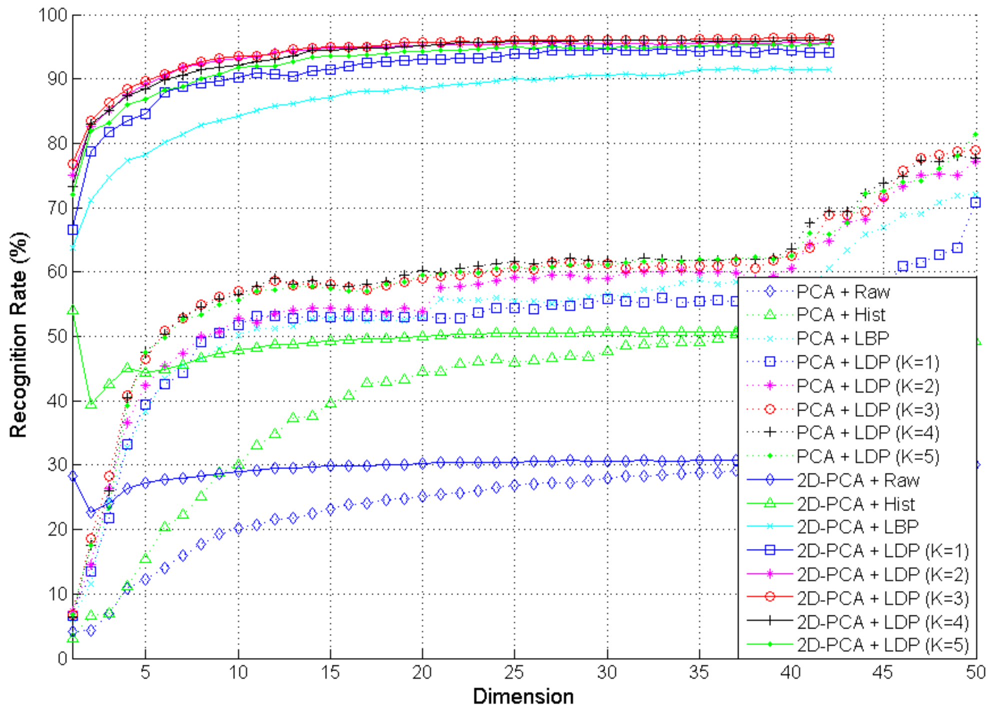

Figure 4. Recognition Rates of Yale B Database as Feature Dimensions

Table 1. Maximum Recognition Rates on Yale B Database

Input Images	**Recognition Approaches**		
	PCA	2D-PCA	Gabor-wavelets based LBP
Raw	30.03%	30.78%	57.14%
Histogram	50.61%	54.09%	**69.50%**
LBP	72.09%	91.54%	X
LDP (K=1)	70.77%	94.60%	X
LDP (K=2)	77.16%	95.72%	X
LDP (K=3)	78.85%	**96.43%**	X
LDP (K=4)	77.96%	96.10%	X
LDP (K=5)	**81.34%**	95.49%	X

3.2. CMU-PIE Database

For the CMU-PIE illumination/light database, each training set comprised of only one images per subject, and the remaining images were used for testing. Similar to the Yale B database, we selected an illumination-invariant image for training, and the remaining illumination-variant images were employed for testing. The recognition results for the CMU-PIE illumination and light database s are shown in Figure 5 and 6, respectively. For the CMU-PIE illumination database, the recognition results of various approaches shown in Table 2. In Table 2, the proposed method showed a maximum recognition rate of 100.0%, when k is 2, 3, 4, and 5, while PCA and Gabor-wavelets based on LBP approaches were 99.85% and 82.20%, respectively. As a result, the recognition accuracy of proposed method showed better performance compared to other methods, and it provide the performance improvement of 17.80% in comparison to Gabor-wavelets based on LBP approach. Table 3 also depicts the recognition results of various approaches for the CMU-PIE light database. Similar to results of CMU-PIE illumination database, the recognition rate of proposed method showed 100.0%. Consequently, we confirmed the effectiveness of the proposed method under varying lighting conditions through these experimental results.

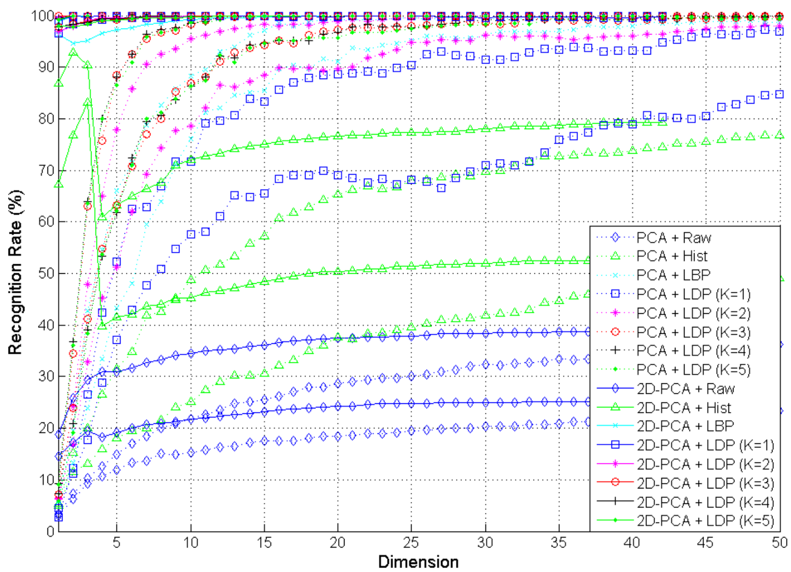

Figure 5. Recognition Rates of CMU-PIE Illumination Database as Feature Dimensions

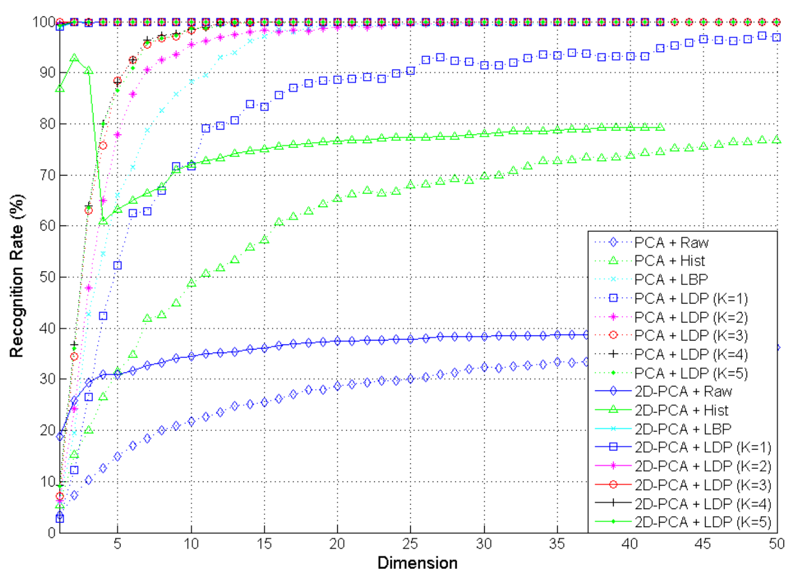

Figure 6. Recognition Rates of CMU-PIE Light Database as Feature Dimensions

Table 2. Maximum Recognition Rates on CMU-PIE Illumination Database

Input Images	Recognition Approaches		
	PCA	2D-PCA	Gabor-wavelets based LBP
Raw	23.38%	25.22%	63.23%
Histogram	49.12%	83.24%	**82.20%**
LBP	98.97%	100.0%	X
LDP (K=1)	84.71%	99.93%	X
LDP (K=2)	98.09%	100.0%	X
LDP (K=3)	99.71%	**100.0%**	X
LDP (K=4)	**99.85%**	100.0%	X
LDP (K=5)	99.49%	100.0%	X

Table 3. Maximum Recognition Rates on CMU-PIE Light Database

Input Images	Recognition Approaches		
	PCA	2D-PCA	Gabor-wavelets based LBP
Raw	36.20%	39.21%	94.11%
Histogram	76.82%	79.34%	**99.08%**
LBP	100.0%	100.0%	X
LDP (K=1)	97.20%	100.0%	X
LDP (K=2)	100.0%	100.0%	X
LDP (K=3)	**100.0%**	**100.0%**	X
LDP (K=4)	100.0%	100.0%	X
LDP (K=5)	100.0%	100.0%	X

4. Conclusions

In this paper, we proposed a novel approach for achieving the illumination invariant face recognition via LDP image. Especially, we presented the face recognition methodology that utilizes the transformed image obtained from LDP as the direct input image of 2D-PCA, unlike that most of previous works used the local pattern descriptors to acquire the histogram features. The proposed method has an advantage that the illumination effects can be degraded by LDP descriptor and 2D-PCA is also more robust against illumination variation than global features. The performance evaluation was performed on the Yale B database and CMU-PIE database, and the proposed method showed the best recognition accuracy compared to different approaches. Through experimental results, we confirmed the effectiveness of the proposed method under illumination varying environments.

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