LETTER

Face Recognition Using LBP Eigenfaces

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SUMMARY In this paper, we propose a simple and efficient face representation feature that adopts the eigenfaces of Local Binary Pattern (LBP) space, referred to as the LBP eigenfaces, for robust face recognition. In the proposed method, LBP eigenfaces are generated by first mapping the original image space to the LBP space and then projecting the LBP space to the LBP eigenface subspace by Principal Component Analysis (PCA). Therefore, LBP eigenfaces capture both the local and global structures of face images. In the experiments, the proposed LBP eigenfaces are integrated into two types of classification methods, Nearest Neighbor (NN) and Collaborative Representation-based Classification (CRC). Experimental results indicate that the classification with the LBP eigenfaces outperforms that with the original eigenfaces and LBP histogram.

key words: *LBP, eigenfaces, PCA, face recognition*

1. Introduction

In the past several decades, various face recognition methods have been proposed. One of the famous approaches is the eigenfaces method [1], which projects face images onto a feature space that spans the significant variations among the training face images. While the Principal Component Analysis (PCA) extracts a subspace in which the variation is maximized, the unwanted variation such as the change of illumination or facial expression can result in the performance degradation of face recognition. In general, the variation between images of the same face due to illumination change is almost always larger than the image variation due to change in face identity [2]. Therefore, such methods using the pixel-value-based image space are not efficient for face recognition for two reasons. First, the image space is easily influenced by the illumination change which introduces unwanted variation. Second, the eigenfaces methods ignore the local characteristics of the face image while preserving the global structure of the images. To solve this problem, in this paper, we employ the LBP eigenfaces for face recognition. The face images are first mapped into the LBP feature space, and then PCA is applied in the LBP feature space to generate the LBP eigenfaces feature for face recognition. The experimental results demonstrate that our LBP eigenfaces are efficient and robust for face recognition.

2. LBP Eigenfaces

Local Binary Pattern (LBP), has been widely used in face recognition [3] as a local descriptor. Figure 1 illustrates an example of the basic LBP operation, where a binary label is assigned to every pixel of an image by thresholding each pixel in the 3×3-neighborhood with the center pixel value. Figure 2 (a) and (b) show two pairs of face images of two different persons captured under the high and low illuminations from the Extended Yale B database [4] and their corresponding LBP images, respectively. Note that even when the illumination of the original images changes dramatically, we can easily identify the faces of different persons by the LBP images. In general, LBP is not only insensitive to grayscale changes, but also well describes micropatterns of the facial image, such as flat areas, spots, lines, and edges [3]. Thus, LBP eigenfaces generated from the LBP space can avoid the unwanted variations due to lighting conditions as well as capture the variations of the micropatterns in the facial images.

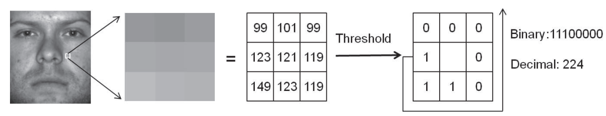
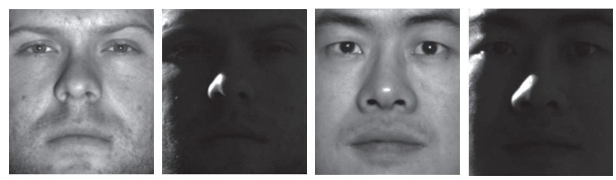


Fig. 1 The basic LBP operator. The binary sequence output is 11100000, which is finally converted into the decimal number, 224.



(a)

(b)

Fig. 2 (a) Two pairs of face images of two different persons captured under high and low illumination from the Extended Yale B face database, (b) Corresponding LBP images of (a).

Next, we describe how to calculate LBP eigenfaces. Given a training set of N face images, let $\boldsymbol{I}_i$ represent the i-th face image with $P \times Q$ pixels. The corresponding LBP image $\boldsymbol{I}_i^{LBP}$ is obtained by applying the basic LBP operation shown

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Fig. 3 First 10 eigenfaces of the original eigenfaces and the LBP eigenfaces are displayed in the first and second rows, respectively.

in Fig. 1 to $\boldsymbol{I}_i$. Then a column vector $\boldsymbol{x}_i^{LBP}$ with $P \times Q$ elements is constructed by concatenating each column of $\boldsymbol{I}_i^{LBP}$ orderly. Once the LBP feature space, $\{\boldsymbol{x}_1^{LBP}, \boldsymbol{x}_2^{LBP}, \ldots, \boldsymbol{x}_N^{LBP}\}$, is obtained, the average vector of the LBP images is calculated by $\boldsymbol{x}_{avg}^{LBP} = \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{x}_i^{LBP}$, and the covariance matrix $\boldsymbol{C}$ can be also computed by

$$\boldsymbol{C} = \frac{1}{N}\boldsymbol{A}\boldsymbol{A}^{\mathrm{T}}, \tag{1}$$

where $\boldsymbol{A} = [\boldsymbol{x}_1^{LBP} - \boldsymbol{x}_{avg}^{LBP}, \boldsymbol{x}_2^{LBP} - \boldsymbol{x}_{avg}^{LBP}, \ldots, \boldsymbol{x}_N^{LBP} - \boldsymbol{x}_{avg}^{LBP}]$. Then the k-th LBP eigenface $\boldsymbol{\mu}_k$ is defined by

$$\boldsymbol{C}\boldsymbol{\mu}_k = \lambda_k\boldsymbol{\mu}_k, \tag{2}$$

where λ_k is the k-th largest eigenvalue of $\boldsymbol{C}$. Each LBP face image can be represented by a linear combination of K LBP eigenfaces as follows,

$$\boldsymbol{x}_i^{LBP} - \boldsymbol{x}_{avg}^{LBP} \approx \omega_1\boldsymbol{\mu}_1 + \omega_2\boldsymbol{\mu}_2 + \ldots + \omega_K\boldsymbol{\mu}_K. \tag{3}$$

The coefficient vector, $\boldsymbol{\omega}^{\mathrm{T}} = [\omega_1, \omega_2, \ldots, \omega_K]$ is used as a K-dimensional feature vector for face recognition, where ω_k is computed by a simple operation,

$$\omega_k = \boldsymbol{\mu}_k^{\mathrm{T}}(\boldsymbol{x}_i^{LBP} - \boldsymbol{x}_{avg}^{LBP}). \tag{4}$$

In order to show the difference between eigenfaces and LBP eigenfaces, the first 10 eigenfaces and LBP eigenfaces computed from the Extended Yale B dataset [4] are illustrated in Fig. 3. It shows that the structure of the discriminative facial parts, such as eyes and mouth are captured explicitly in LBP eigenfaces compared with those in the original eigenfaces.

It is worthwhile to note that, compared with the LBP histogram [3], the LBP eigenfaces implicitly encode the spatial relations of these LBPs, which are not preserved well when constructing the LBP histogram. Thus, the LBP eigenfaces feature is more discriminative than the LBP histogram.

3. Experiments

In this section, we present experiments on publicly available databases for face recognition. The databases are the Extended Yale B database [4], [5] and the AR database [6]. Two classification methods are used for our test, Nearest Neighbor (NN) with the Euclidean distance and Collaborative Representation-based Classification (CRC) [7]. We consider four possible combinations: Eigenfaces with NN (E_NN), LBP Eigenfaces with NN (LE_NN), Eigenfaces with CRC (E_CRC) [7], and LBP Eigenfaces with CRC (LE_CRC). We also implement the LBP histogram [3] in conjunction with NN with Chi-square distance for comparison.

Table 1 Recognition rates in Extended Yale B Database.

Dim	84	150	300
E_NN	67.1%	73.4%	77.1%
LE_NN	99.3%	99.3%	99.3%
E_CRC [7]	95.0%	96.3%	97.9%
LE_CRC	**99.8%**	**99.9%**	**100%**

Table 2 Recognition rates in AR Database.

Dim	84	150	300
E_NN	66.7%	70.2%	71.1%
LE_NN	84.5%	89.2%	89.7%
E_CRC [7]	80.5%	90.0%	93.7%
LE_CRC	**90.6%**	**97.0%**	**97.8%**

The Extended Yale B database [4] consists of 2,414 frontal face images from 38 individuals, which were captured under various illumination conditions. We use the cropped face images with 64×56 pixels [5]. We randomly split the database into two halves. The first half contains 32 images for each person as the training set, the other half is used for testing. Table 1 shows the recognition rate versus the feature dimension for E_NN, LE_NN, E_CRC, and LE_CRC. It can be seen that the adoption of LBP eigenfaces improves the performance of the classifiers. As the dimension of the feature increases, LE_CRC exhibits the perfect recognition performance. Since the illumination variation in the Extended Yale B database is large, it is expected that E_NN can not achieve a good recognition rate. In contrast, the LBP eigenfaces with NN can achieve a recognition rate 99.3%. We also test the LBP histogram [3] on Yale B database with different block partition (5×5, 7×7, 9×9, 11×11). The best recognition rate is 78.8%, when the size of block is 7×7 pixels. Note that dimension of the LBP histogram is more than 18000, which is computationally expensive. Traditionally, when feature is used in conjunction with simple classifiers such as NN, the choice of feature is considered critical to the success of the algorithm. Therefore, it demonstrates that the LBP eigenfaces can capture the more discriminative information for face recognition.

The AR database [6] consists of over 4,000 frontal images from 126 individuals. A subset with illumination and facial expression changes which contains 50 male subjects and 50 female subjects was chosen [7]. For each subject, we use seven images from Session 1 for training, and another seven images from Session 2 for testing. The images are resized to 60×43 pixels. Comparison results are given in Table 2. It is seen that the LBP eigenfaces with both NN and CRC improve the recognition performance remarkably. LBP histogram achieves a recognition rate 66.4% when the size of block is 7×7. Note that LE_CRC can achieve the highest recognition rate of 98.4% when $K = 380$ in our experiments.

To show the robustness of LBP eigenfaces, we perform simulation in various levels of randomly contiguous occlu-

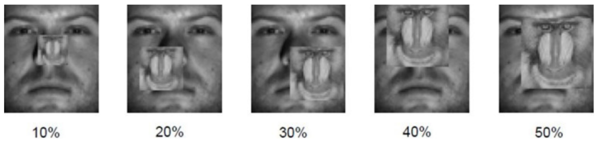

Fig. 4 An example of the various level of occlusion from 0% to 50%. Note that the location of the occlusion is randomly chosen for each test image.

Table 3 Face recognition rates with occlusion.

Method	0%	10%	20%	30%	40%	50%
E_NN	77.1%	73.1%	64.0%	52.0%	42.2%	31.2%
E_CRC	97.8%	90.0%	84.7%	76.6%	66.8%	53.8%
LE_NN	99.3%	99.0%	98.4%	95.6%	88.6%	79.4%
LE_CRC	100%	99.8%	99.7%	99.6%	99.4%	96.9%
LBP histogram	78.8%	76.9%	74.9%	72.3%	66.5%	55.9%

sion [8], from 0% to 50% on the Extended Yale B database as shown in Fig. 4. Experimental results in Table 3 shows that LBP eigenfaces performs well. For the case of 40% occlusion, the performance degradation of LBP eigenfaces is 0.6% with CRC and 10.7% with NN. In contrast, the recognition rates of eigenfaces decrease by 31% with CRC and 34.7% with NN. In addition, the recognition rate of the LBP histogram using NN with the Chi-square distance decreases by 12.3%. The robustness of LBP eigenfaces of occlusion demonstrates that LBP eigenfaces capture the local structure of the face image well.

4. Conclusion

In this paper, we proposed a simple yet very effective feature, namely LBP eigenfaces, for face recognition. LBP eigenfaces encode both local and global structures of the face images by applying the PCA to the LBP space. To demonstrate the efficiency of the proposed LBP eigenfaces, we perform the simulation on the database including the illumination change, facial expression change, and occlusion. Experimental results show that the proposed LBP eigenfaces is a robust and discriminative feature for face recognition.

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