A Novel Image Preprocessing Technique Based on Binary Patterns

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Abstract. This paper proposes a novel image preprocessing technique based on binary patterns for illumination invariant face recognition. The face recognition system comprised of a centralized gradient pattern image and facial features based on image covariance. The centralized gradient pattern image is obtained by AND operation of a modified local binary pattern image and a modified local directional pattern image, and it is then utilized as input image for the facial feature extraction based on image covariance. To verify the proposed face recognition method, the performance evaluation was carried out using various recognition algorithms on the Yale B and extended Yale B face databases. Through the experimental results, the proposed method showed the best recognition accuracy compared to various approaches.

Keywords: Image Preprocessing, Face Recognition.

1 Introduction

This paper proposed an image preprocessing technique for illumination-robust face recognition method. Here, the image preprocessing technique denotes the centralized gradient pattern (CGP), and facial features based on image covariance, i.e. two-dimensional principal component analysis (2D-PCA) and an alternative two-dimensional principal component analysis (A2D-PCA), are used for face recognition. The CGP is one kind of binary pattern transform operators, and it is obtained by AND operation between modified local binary pattern images. To verify the proposed face recognition method, the performance evaluation was carried out using various recognition algorithms on the Yale B and extended Yale B illumination databases, and we will show the effectiveness of the proposed method in experimental results.

2 Related Works

To overcome the problem caused by illumination variation on face, various approaches have been introduced, such as preprocessing and illumination
normalization techniques, illumination invariant feature extraction techniques, and 3D face modeling techniques. Among abovementioned approaches, local binary pattern (LBP) [1] has received increasing interest for face representation in general [2]. LBP was originally proposed for texture description [3], and has been widely exploited in many applications such as video retrieval, aerial image analysis, and visual inspection. In addition, centralized binary pattern (CBP) [4] and center-symmetric local binary pattern (CS-LBP) [5] introduced for facial expression recognition and image representation. Compared to the original LBP, CBP and CS-LBP produce less binary units, and thus reducing the histogram feature vector length. More recently, the local directional pattern (LDP) method was introduced for a more robust facial representation [6]. 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.

3 Novel Image Preprocessing

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. Also, the CBP operator compares pairs of neighbors which are in the same diameter of the circle, and also compares the central pixel with the mean of all the pixels. The CS-LBP operator is computed by only considering the corresponding patterns of symmetric pixels. While the binary patterns such as LBP, CBP and CS-LBP use the information of intensity changes around pixels, the LDP operator is calculated by comparing the relative edge response values of a pixel by using Kirsch edge detector. Since the presence of a corner or an edge shows high response values in some particular directions, the original LDP operator only considers most prominent directions of \( k \) number with high response values.

Based on these previous works, we device centralized gradient pattern which is more robust to illumination changes on facial image. The CGP operator is obtained by AND operation of a modified CS-LBP (MCS-LBP) image and a modified LDP (MLDP) image. Here, the MCS-LBP operator is the version of emphasizing the diagonal component, and it is given by

\[
MCS\text{-LBP} = s(g_0 - g_4)\times 2^0 + s(g_2 - g_6)\times 2^1 + s(g_1 - g_5)\times 2^2 + s(g_3 - g_7)\times 2^3. \tag{1}
\]

Also, the MLDP is the modification version of LDP, in which it takes into account all directions of 3x3 neighborhood pixel while LDP only considers most prominent directions of \( k \) number with high response values. In other words, the MLDP operator undergoes same procedures of LBP except to computation step of edge response values. Consequently, the CGP image is obtained by AND operation of MCS-LBP image and MLDP image, and the CGP image is used as input image of the recognition algorithms such as principal component analysis (PCA), linear discriminant analysis (LDA), 2D-PCA, and A2D-PCA.
4 Recognition

2D-PCA views an image as a matrix. Consider an \( m \) by \( n \) image matrix \( A \). Let \( X \in \mathbb{R}^{m \times d} \) 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 \( A_k \) \((k = 1, 2, \ldots, M)\), and the average image is denoted as \( \overline{A} = 1/M \sum_k A_k \). Then, the image covariance matrix, \( G \) is given by

\[
G = \frac{1}{M} \sum_{k=1}^{M} (A_k - \overline{A})^T (A_k - \overline{A}).
\]  

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

\[
Y_k = (A - \overline{A})X_k, \quad k = 1, 2, \ldots, d.
\]  

Similar to 2D-PCA, an alternative 2D-PCA (A2D-PCA) is also presented for face representation and recognition. While 2D-PCA is essentially working in the row direction of images, the A2D-PCA is working in the column direction of images. When compared to 2D-PCA, the difference point of A2D-PCA is that the covariance matrix is computed by

\[
G = \frac{1}{M} \sum_{k=1}^{M} (A_k - \overline{A})^T (A_k - \overline{A}).
\]

5 Experiments

To verify the recognition performance of the proposed face recognition system, we have implemented and tested it with two popular face databases: Yale B, and extended Yale B illumination databases. Here, the face region on each databases are obtained according as following procedures. The center of each eye was manually located and the input image was rotated to be horizontally aligned using rotated-angle information of both eyes. Then, each face image was cropped by using boundary information and rescaled to a resolution of \( 60 \times 54 \) pixels. Fig. 1 show an example of sample face images for the Yale B database. The performance evaluation of
The proposed approach was carried out using well-known recognition approaches such as PCA, LDA, 2D-PCA, A2D-PCA and Gabor-wavelets based on LBP. In the following, we present the testing results on each database for different recognition approaches.

Next, we investigated the recognition rates of proposed method with Yale B, and extended Yale B databases. For the Yale B database, we employ 640 face images for 10 subjects representing 64 illumination conditions under the frontal pose, and we also used 2,414 face images for 38 subjects in extended Yale B database, in which subjects comprised 10 individuals in the original Yale B database and 28 individuals in the extended Yale B database. During performance evaluation, we partitioned the face database into training and testing sets. For the Yale B and extended Yale B databases, each training set comprised of seven images per subject, and the remaining images were used to test. In result, we show the maximum recognition rates for the Yale B and extended Yale B databases in Table 1 and 2, respectively. The proposed approach using CGP image and 2D-PCA showed best recognition rates of 99.64% and 97.84% for the Yale B and extended Yale B, respectively. Note that the recognition results using CGP image and A2D-PCA are similar to those of proposed method. Consequently, we confirmed the robustness and effectiveness of the proposed method under varying lighting conditions through these experimental results.

Table 1. Maximum recognition rates on Yale B database.

<table>
<thead>
<tr>
<th>Input Images</th>
<th>Recognition Approaches</th>
<th>PCA</th>
<th>LDA</th>
<th>2D-PCA</th>
<th>A2D-PCA</th>
<th>Gabor-wavelets based on LBP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw</td>
<td>41.07%</td>
<td>54.64%</td>
<td>41.61%</td>
<td>41.25%</td>
<td>66.66%</td>
<td></td>
</tr>
<tr>
<td>Histogram</td>
<td>68.21%</td>
<td>57.14%</td>
<td>69.29%</td>
<td>67.32%</td>
<td>86.31%</td>
<td></td>
</tr>
<tr>
<td>LBP</td>
<td>95.89%</td>
<td>66.79%</td>
<td>97.68%</td>
<td>97.86%</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>CS-LBP</td>
<td>85.18%</td>
<td>47.32%</td>
<td>88.39%</td>
<td>88.57%</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>LDP</td>
<td>99.11%</td>
<td>71.25%</td>
<td>99.64%</td>
<td>99.64%</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>CGP</td>
<td>99.29%</td>
<td>93.04%</td>
<td>99.64%</td>
<td>99.64%</td>
<td>X</td>
<td></td>
</tr>
</tbody>
</table>
Table 2. Maximum recognition rates on extended Yale B database.

<table>
<thead>
<tr>
<th>Input Images</th>
<th>Recognition Approaches</th>
<th>Gabor-wavelets based on LBP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PCA</td>
<td>LDA</td>
</tr>
<tr>
<td>Raw</td>
<td>30.22%</td>
<td>52.77%</td>
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<tr>
<td>Histogram</td>
<td>50.61%</td>
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<tr>
<td>LBP</td>
<td>79.89%</td>
<td>53.38%</td>
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<tr>
<td>CS-LBP</td>
<td>63.44%</td>
<td>43.14%</td>
</tr>
<tr>
<td>LDP</td>
<td>83.88%</td>
<td>57.66%</td>
</tr>
<tr>
<td>CGP</td>
<td>93.66%</td>
<td>80.59%</td>
</tr>
</tbody>
</table>

6 Conclusion

In this paper, we proposed a novel face recognition approach using the CGP image and recognition algorithms based on image covariance. In particular, we presented the face recognition methodology that utilizes the CGP image as the direct input image of conventional recognition algorithms, unlike that most of previous works used the local pattern descriptors to acquire the histogram features. From the experimental result, the proposed approach showed best recognition rates of 99.64% and 97.84% for the Yale B and extended Yale B illumination databases, respectively. As a result, we confirmed the robustness and effectiveness of the proposed method under varying lighting conditions through experimental results.

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References
