IMPROVING INDOOR AND OUTDOOR FACE RECOGNITION USING UNIFIED SUBSPACE ANALYSIS AND GABOR FEATURES

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ABSTRACT

Lighting variation is one of the major problems for face recognition. Most of the current face recognition studies on lighting problem are based on the face image set taken under controlled laboratory lighting or normal indoor lighting. In the recent FRVT 2002 test, it is found that the best face recognition systems are not sensitive to normal indoor lighting changes, but have a significant drop in performance on the outdoor probe face image set. This clearly indicates that recognition of faces in outdoor images needs to be a focus of future research. In this paper, we address the lighting variation problem using several simple and practical techniques. Using the unified subspace method in combination with wavelet local features and appropriate training data selection, we improve the indoor and outdoor face recognition significantly.

1. INTRODUCTION

One of the major problems in face recognition is the lighting variation, which can substantially change the face appearance. Many studies on the lighting problem can be found in literature [1][2][3]. They are all based on face image sets taken under controlled laboratory lighting or normal indoor lighting. However, in the recent Face Recognition Vendor Test 2002 (FRVT 2002) [4], it is found that the best face recognition systems are not sensitive to normal indoor lighting changes (with or without overhead fluorescent lighting), instead their performance drops significantly on the outdoor probe face image set. This indicates that recognition of faces in outdoor images needs to be a focus of future study. Outdoor lighting may cause a more complicated face appearance variation than indoor and controlled lighting, since it involves multiple light sources from sky and the reflectance of other objects, and the human faces may also be placed in the shadows of other objects.

Most of the existing approaches try to solve the lighting problem by using the Lambertian reflectance model to describe the face image variation under different lighting conditions. If all the shadowing effect is ignored, the set of images of one face lies in a 3D linear space, which can be reconstructed using three training samples taken under different lighting conditions [1]. Basri et. al. [2] proved that this image set can be approximated as a 9D linear space considering the attached shadows but ignoring the cast shadows. Georghiades et. al. [3] proposed an illumination cone with infinite dimension accounting for attached shadows and cast shadows. Under outdoor condition, these approaches will face great challenge. There are multiple light sources, and the reflectance from each lighting source may be affected by the cast shadows caused by other objects and other parts of the face. This may produce a complicated variation on face appearance.

In this paper, we address the lighting variation by a more practical approach. Using an unified subspace method we recently developed [5], in combination with wavelet local features and appropriate training data selection, we improve the indoor and outdoor face recognition significantly. Since most existing database only contain photos of controlled lighting and few have uncontrolled indoor and outdoor images, we first design a database containing images under controlled, indoor, and outdoor lighting conditions. Through a systematic set of experiments we evaluate how each step of our method can improve the recognition performance under different lighting conditions.

2. UNIFIED SUBSPACE ANALYSIS

PCA [6], Bayes [7], and LDA [8] are three of the most popular subspace face recognition methods. They all have some ability to reduce the lighting variation. In our previous work [5], we unified them under the same framework and proposed a unified subspace analysis method integrating PCA, Bayes and LDA as three steps.

We first model the difference between two face images as three components: intrinsic difference that discriminates different face identity, transformation difference arising from all kinds of transformations such as expression and lighting changes, and noise which randomly distributes in the face images. A successful face recognition algorithm should reduce the transformation difference as much as possible without sacrificing much of intrinsic difference. Based on this face difference model, we unified the above three most popular subspace face recognition methods under the same framework, and proposed a unified subspace analysis method integrating them as three steps. By adjusting the three subspace dimensions, the new method can best extract the intrinsic difference discriminating different face identity, while reduce the noise and the transformation difference caused by lighting changes:

(1) Project face vectors to PCA subspace and adjust the PCA dimension (*dp*) to reduce most noise.
(2) Apply Bayesian analysis in the reduced PCA subspace and adjust the dimension (*di*) of intrapersonal subspace to reduce the transformation difference.
(3) Project all the face class centers onto the *di* intrapersonal eigenvectors, and then normalize the projections by intrapersonal eigenvalues to compute the whitened class centers. Apply PCA on the whitened class centers to compute a discriminant feature vector of dimension *dl*. The face class is recognized using the *dl* discriminant features.

In this unified subspace analysis method, we could improve each step of subspace analysis by choosing the optimal subspace dimension, and achieve better recognition performance than standard subspace methods. Face transformation caused by lighting changes can be significantly reduced.

3. GABOR LOCAL FEATURE

Gabor wavelet based approach seeks to utilize a different representation of face images that are relatively insensitive to lighting changes for recognition. In Elastic Bunch Graph Matching [9], local wavelet features are extracted by convolving the image with a set of Gabor-like filters. A family of Gabor kernel is the product of a Gaussian envelope and a plane wave, defined as

$$\psi_{\vec{k}}(\vec{x}) = \frac{\|\vec{k}\|}{\delta^2} \cdot e^{-\frac{\|\vec{k}\|^2 \|\vec{x}\|^2}{2\delta^2}} \cdot \left[e^{i\vec{k}\cdot\vec{x}} - e^{-\frac{\delta^2}{2}} \right]. \qquad (1)$$

Here $\vec{x} = (x, y)$ is the variable in spatial domain and $\vec{k}$ is the frequency vector, which determines the scale and the orientation of Gabor kernels,

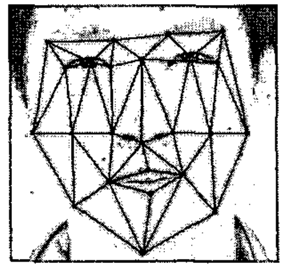

Figure 1. Face Graph Model.

$$\vec{k} = k_s e^{i\phi_d}, \qquad (2)$$

where $k_s = \frac{k_{\max}}{f^s}$, $k_{\max} = \frac{\pi}{2}$, $f = 2$, $s = 0,1,2,3,4$, and

$$\phi_d = \frac{\pi \cdot d}{8}, for\ d = 0,1,2,3,4,5,6,7.$$

We choose 5 scales and 8 orientations in our study. The term $\exp(-\sigma^2/2)$ is subtracted in order to make the kernel DC-free, thus become insensitive to illumination.

Given an image $I(\vec{x})$, its Gabor transformation at a particular position $\vec{x}_0$ is computed by a convolution with the Gabor kernels

$$(\psi_{\vec{k}} * I)(\vec{x}_0) = \int \psi_{\vec{k}}(\vec{x}_0 - \vec{x}) I(\vec{x}) d^2(\vec{x}). \qquad (3)$$

We design a face graph model with 23 nodes on critical fiducial points as shown in Figure 1 [10]. A set of 40 Gabor features can be obtained for each fiducial point. Since phase changes drastically with translation, only 40 magnitude features are used in a local feature vector f_{p_i}. The face image is finally represented by a large Gabor feature vector combining 23 local vectors,

$$V_{Gabor}^T = \left[f_{p_1}^T, f_{p_2}^T, \dots f_{p_{35}}^T \right]. \qquad (4)$$

4. STUDY ON DIFFERENT LIGHTING CONDITIONS

4.1. Data Set

We collect a database containing 378 frontal face images for 23 face classes taken under three different lighting conditions: 69 images under controlled lighting, 135 images under indoor lightings and 174 images under outdoor lighting. Some examples are shown in Figure 2. All the face images for each face class are taken in the same day with no expression changes. So the major intrapersonal variation is caused by lighting changes. For controlled lighting condition, there are three images for each face class under ambient lighting, right lighting and left lighting.

4.2. Evaluation Methods

Based on this database, we evaluate the performance of the unified subspace analysis and Gabor features on different lighting conditions. Subspace analysis is based on the holistic face appearance feature. In preprocessing, the images are normalized for scaling, translation, and rotation, such that the eye centers are in fixed positions. A 81×121 mask template is used to remove the background and most of the hair. Gabor features are extracted from the local patches around fiducial points. As shown in Figure 1, 23 fiducial points are selected, excluding the hair region. For each face class, one face image taken under the controlled ambient lighting is used for reference, and the remaining face images are used for probe. Evaluation is performed based on the following considerations.

4.2.1. Training Sets

We use different training sets to improve the performance of unified subspace analysis. We evaluate its performance on five kinds of training sets: controlled lighting, indoor lighting, outdoor lighting, uncontrolled lighting (indoor + outdoor), and all lightings (controlled + indoor + outdoor). The "leaving-one-out" methodology is adopted. For each probe image, all the face images belonging to its class are excluded from the training set.

4.2.2. Photometric Normalization

For subspace analysis, two kinds of widely used global photometric normalization methods are applied to face images as preprocessing: normalizing face vector into unit norm and histogram equalization. We will evaluate their performance on improving different lighting conditions.

4.2.3. Combining Subspace Analysis and Gabor features

Gabor filtering also can be viewed as a kind of photometric preprocessing to the face image. In order to reduce the influence of lighting changes as much as possible, we first investigate the performance of each of the four approaches: unified subspace analysis, training set selection, photometric normalization, and Gabor features. We then combine the most effective methods together to achieve the best performance.

5. EXPERIMENTAL RESULTS

Table 1 reports the recognition accuracies of unified subspace analysis on three lighting sets using different training sets. Directly comparing the face appearance using Euclid distance without subspace analysis, the performance on the three lighting conditions is poor, all below 40%. This shows that lighting variation has great effect on recognition and the data set is quite difficult to classify. Unified subspace analysis can significantly improve the recognition accuracies. The uncontrolled lighting training set including indoor and outdoor images has the best performance on all the three testing sets. It can also effectively reduce the controlled lighting variation. Using the face images taken under controlled lighting condition for training, the controlled lighting variation can be effectively reduced, but it cannot deal with the indoor and outdoor lighting changes. This shows the importance of having a proper training dataset for subspace analysis. Especially, the data set should contain a wide range of variation including both indoor and outdoor images, instead of only the simple controlled lighting cases.

(a) Controlled lighting

(b) Indoor lighting

(c) Outdoor lighting

Figure 2. Face image examples taken under different lighting conditions.

In the following experiments, we always use the uncontrolled lighting training set for subspace analysis. Table 2 reports the subspace analysis performance using different photometric normalizations as preprocessing. We found that the global photometric normalizations can improve the indoor testing set, but are less effective to controlled and outdoor lighting variations. This may be due to the fact that indoor lighting tends to be ambient, thus its variation is more uniform and can be reduced by global normalization such as scaling and histogram equalization.

Gabor filtering can also be viewed as a kind of photometric normalization based on local patches. As

Table 1. Recognition accuracies of subspace analysis on different lighting conditions using different training sets.

Testing sets	Euclid distance	Subspace analysis with different training sets				
		Controlled	Indoor	Outdoor	Uncontrolled	All
Controlled	39.13	93.48	97.83	91.30	97.83	97.83
Indoor	32.59	66.67	82.96	82.96	82.96	80.00
Outdoor	32.18	62.64	72.99	74.71	79.31	76.44

Table 2. Recognition accuracies of subspace analysis using different photometric normalization.

Testing Set	No normalize	Unit norm	Histogram equalization
Controlled	97.83	97.83	76.09
Indoor	82.96	89.63	91.11
Outdoor	79.31	78.74	78.74

Table 3. Recognition accuracies using subspace analysis and Gabor features.

Testing Set	Euclid distance	Gabor	Subspace	Gabor + Subspace
Controlled	39.13	100	97.83	100
Indoor	32.59	91.85	89.63	94.07
Outdoor	32.18	71.26	79.31	86.21

shown in Table 3, Gabor feature is a good representation of face image on overcoming the lighting problem. We try to apply the global subspace analysis to the local Gabor features. It has the best performance on all the three kinds of lighting conditions. Therefore, by combining the unified subspace analysis with proper training data and the Gabor features we can significantly improve the recognition performance of all three lighting conditions. Notice that the absolute accuracies in the results are not important. We are more interested in the observations that are reflected by the relative performance comparing different techniques.

6. DISCUSSION AND CONCLUSION

In this paper, we investigate four simple and practical techniques for reducing lighting variations, a major problem in face recognition. Based on the experiments on controlled, indoor, and outdoor lighting conditions, we arrive at the following conclusions:

(1) Both unified subspace analysis and wavelet features can reduce the lighting variation in face recognition. Outdoor probe set is more difficult than that taken under controlled and indoor lightings.
(2) The subspace computed from the controlled lighting training set can effectively reduce the controlled lighting changes, but it cannot deal with the uncontrolled indoor and outdoor lighting changes.
(3) Global photometric normalization can improve the indoor face image recognition, but it is not much helpful for controlled and outdoor lighting sets.
(4) Subspace analysis on local Gabor features has the best performance for all the three lighting conditions.

These observations should be helpful for design of face recognition systems that are more robust to lighting variations. Of course, more experiments on a much larger data set are needed to further confirm the observation and to develop better algorithms.

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