Illumination-Robust Face Recognition based on Gabor Feature Face Intrinsic Identity PCA Model

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Abstract: - Robust face recognition under various illumination environments is essential for successful commercialization. Feature-based face recognition relies on a good choice of feature vectors. However, there is no feature vector invariant under illumination changes even though some feature vector such as Gabor feature vector is relatively robust to variations of illumination. Also, illumination normalization techniques cannot eliminate illumination effects completely. In this paper, we propose an illumination-robust face recognition method based on the face Gabor intrinsic identity PCA model. We first analyze face Gabor feature vector space and construct a face Gabor intrinsic identity PCA model which is independent of illumination effects and propose a face recognition method based on it. Through experiments, it is shown that the proposed face recognition based on face Gabor intrinsic identity PCA model performs more reliably under various illuminations and pose environments.

Key-Words: Face Recognition, Illumination-robustness, Gabor feature vector, face intrinsic identity

1 Introduction
Face recognition has numerous applications including access control, security and surveillance, human computer interfaces and etc. Thus, during the last decade, significant research efforts have been poured into face recognition. However, robust face recognition under various illumination environments turns out to be difficult to achieve [1]. It is now well known that variation of illumination conditions can change face appearance dramatically so that the variations between the images of the same face due to illumination can be larger than image variations due to change in face identity [2]. In the past, there have been proposed several approaches to cope with the effects of illumination variations on face recognition. Early works in this regard focused on finding feature vectors that are insensitive to changes in illumination. But, it is now clarified that there is no feature vector invariant under illumination changes [3] even though some feature vectors such as Gabor feature vector are relatively robust to variations of illumination [4]. Another approach is to seek an efficient method to compensate for illumination changes. Retinex theory [5] and anisotropic smoothing-based normalization method [6] have been proposed as this illumination normalization approach. In these methods, real image \( I(x, y) \) is regarded as product of reflectance \( R(x, y) \) and illumination \( L(x, y) \), that is, \( I(x, y) = R(x, y)L(x, y) \) [7]. Reflectance is the amount of light reflected from the surface of the object and is an intrinsic property of an object. Since reflectance is independent of illumination, reflectance image is illumination normalized and can be successfully used for illumination invariant face recognition. Gross and Bravovic[6] estimates reflectance image and illumination image based on the assumption that illumination is usually supposed to change smoothly across the object so that illumination is more responsible for low frequency property of real image while reflectance is more responsible for high frequency property of real image. This assumption does not hold for face image since face image can have cast shadows due to the non convexity of face. Thus, the illumination effects cannot be completely
eliminated from the estimated reflectance image by the anisotropic smoothing-based illumination normalization method. One promising approach to cope with the effects of illumination is to model illumination and reflectance. Under the convex Lambertian reflectance face model, it was shown in [8] that the set of n-pixel images of a face in fixed pose under all lighting conditions consists of a convex cone in $\mathbb{R}^n$. Also, through empirical observations [9] or signal processing theory [10] it is found that this convex illumination can be well-approximated by a low-dimensional linear subspace. However, the illumination cone model cannot still handle the cast shadows which can exist in the real face images. In this paper, we analyze face Gabor feature space of real face images and construct an orthogonal decomposition of the face Gabor feature space into face Gabor intrinsic identity subspace and face Gabor illumination subspace. The face Gabor illumination subspace is constructed so that the variations of feature vectors due to illumination changes are completely reflected on the subspace. On the other hand, the face Gabor intrinsic identity subspace is constructed so as to be completely decoupled from the effects of illumination changes. Thus, if the decomposition is accomplished properly, the projection of the face Gabor feature vector into the face Gabor intrinsic identity subspace becomes independent of the illumination changes so that it can be employed for illumination-robust face recognition. The adopted feature vector is a Gabor feature vector obtained by applying Gabor wavelet kernels into grid points of face images. Gabor feature vector is well known for its relative insensitivity to illumination changes [4]. Since the face image set used for constructing face Gabor feature space includes real face images with cast shadows, the face recognition based on the constructed face Gabor feature intrinsic identity subspace will show robustness to illumination changes, which is verified through experiments. The rest of the paper is organized as follows. Section 2 reviews the technical background for this paper: Gabor wavelet, Gabor jet, face Gabor feature vector, and anisotropic smoothing-based illumination normalization method. Section 3 describes the construction of face Gabor illumination subspace and face Gabor intrinsic identity subspace orthogonal to the face Gabor illumination subspace. Also, a face recognition method based on the face Gabor intrinsic identity subspace is explained. Experiment results are discussed in Section 4, and finally the conclusion is presented in Section 5.

2 BACKGROUNDS

2.1 Gabor wavelet and Face Gabor feature vector

The Gabor features are known as one of the best features for face recognition since they are relatively robust to variations of illumination, image distortion, and rotation [4].

The Gabor wavelet kernels used in this paper are represented as

$$W(x, y, \theta, \lambda, \sigma) = e^{\frac{-1}{\sigma^2}} e^{-i \lambda \cdot \theta} \cdot$$

where $x(x, y)^T$, wave vector $\mathbf{k}$ is given as

$$\mathbf{k} = \left(2\pi \cos \theta \frac{\lambda}{\lambda}, 2\pi \sin \theta \frac{\lambda}{\lambda}\right)^T,$$

$\theta$ represents wavelet direction, $\lambda$ represents wave length, $\sigma$ in (1) represents the size of Gaussian, and is proportional to $\lambda$. In this paper, we consider 40 Gabor wavelet kernels obtained by $\theta \in \{0, \frac{\pi}{8}, \frac{\pi}{8}, \frac{3\pi}{8}, \frac{3\pi}{8}, \frac{5\pi}{8}, \frac{5\pi}{8}\}$ and $\lambda \in \{4\sqrt{2}, 8\sqrt{2}, 16\}$ and $\sigma = \lambda$ in (1). The Gabor feature coefficient $J_k(x, y)$ obtained by convolving k-th one among the above 40 Gabor wavelet kernels with $I(x, y)$ (the image intensity at $(x, y)$) can be also represented as $J_k(x, y) = a_k(x, y)e^{i\phi_k(x, y)}$ with magnitude $a_k(x, y)$ and phase $\phi_k(x, y)$. In this paper, magnitude Gabor jet at the location $(x, y)$, $G(x, y)$ is defined as the vector consisting of the magnitudes of Gabor feature coefficients, $a_k(x, y)$ ($k = 1, \cdots, 40$), that is

$$G(x, y) = (a_1(x, y), a_2(x, y), \cdots, a_{40}(x, y))^T$$

($T$ means transpose).

Now, we define the face Gabor feature vector for a face A, $G(A)$, with n points as the vector consisting of n magnitude Gabor jets as follows:

$$G(A) = (G(x_1, y_1)^T, \cdots, G(x_n, y_n)^T)^T$$

In this paper, we calculate face Gabor feature vectors for face images of size 256x256 where n points are 13x15 grids points as shown in Fig. 1.
2.2 Anisotropic smoothing-based illumination normalization

In general, an image \( I(x, y) \) acquired by a camera is regarded as the product of two components, reflectance \( R(x, y) \) and illumination \( L(x, y) \), that is \( I(x, y) = R(x, y) \times L(x, y) \) [7]. Illumination is the amount of light falling on the object due to the light source. Reflectance is the amount of light reflected from the surface of the object, is an intrinsic property of an object independent of illuminations. Thus, the reflectance face image can be utilized for face recognition which works reliably under illumination variations.

Computing the reflectance and the illumination from real images is, in general, an ill-posed problem. However, on the assumption that illumination is close to the original image and but contains a smoothing constraint, Gross and Brajovic [6] found an approximate solution of illumination by minimizing the following cost function:

Fig. 2 shows original real images, reflectance images and illumination images obtained by the anisotropic smoothing based-illumination normalization. In Fig. 2, one can see the anisotropic smoothing-based illumination normalization method cannot separate reflectance from illumination completely and the reflectance images (such as the 3rd and 4th reflectance images in Fig. 2) obtained by the anisotropic smoothing contains some of illumination effects.

Where \( t \) is a face Gabor feature vector, \( \mu \) is the average of the face Gabor feature vectors in the set, and \( \Phi \) is the matrix whose column vectors are face PCA Gabor mode vectors.

If \( \Phi \) is constructed so that it is orthogonally decomposed into two parts, \( \Phi_{\text{illum}} \) which reflects illumination variations and \( \Phi_{\text{identity}} \) which reflects only face intrinsic identities, then (3) can be represented [11] as

\[
t = \mu + \Phi_{\text{identity}} b_{\text{identity}} + \Phi_{\text{illum}} b_{\text{illum}}
\]

Hence the orthogonal decomposition means \( \Phi_{\text{identity}} \perp \Phi_{\text{illum}} \), that is, the subspace spanned by \( \Phi_{\text{identity}} \) is orthogonal to the subspace spanned by \( \Phi_{\text{illum}} \). Since the subspace spanned by \( \Phi_{\text{identity}} \) is totally separated from the illumination affected subspace spanned by \( \Phi_{\text{illum}} \), the projection coefficients \( b_{\text{identity}} \) obtained by the projection of face Gabor feature vector into the subspace spanned by \( \Phi_{\text{identity}} \) are utilized as the feature vector which is not affected by illumination variations and reflects only intrinsic identity of each face. In this paper, we call (4) as face Gabor feature space intrinsic PCA model, \( \Phi_{\text{identity}} \) as face Gabor intrinsic identity PCA model and \( \Phi_{\text{illum}} \) as face Gabor illumination PCA model.

Constructing a face Gabor feature space intrinsic PCA model (4) directly from a face image set is not easy. Since PCA produces PCA mode vectors showing major variations among data set, one may need to build a face image set where variations of identities and illuminations are composed properly enough to be able to construct a face Gabor feature space intrinsic PCA model (4). But, it is very difficult to build such a face image set that it can produce a face Gabor feature space intrinsic PCA model (4).

3.2 Construction of Face Gabor feature Space Intrinsic PCA Model

Practically, we take a two-step approach in constructing the face Gabor feature space intrinsic PCA model (4) where we first build face Gabor intrinsic identity Model and illumination Model \( \Phi_{\text{identity}} \) and \( \Phi_{\text{illum}} \) respectively and combine two to construct a face Gabor feature space intrinsic PCA model.
3.2.1 Construction of a candidate face Gabor intrinsic identity PCA model

In order to construct a face Gabor intrinsic identity PCA model, one needs to build a face image set where all face images have uniform and good illumination so that the face images in the set do not have effect and variations in illumination. Thus, if one applies PCA to face Gabor feature vectors extracting from such a face image set with uniform and good illumination, it will produce PCA modes which mainly reflect face Gabor intrinsic identities. Thus, one can assume that \( b_{\text{illum}} = 0 \) for this face image set. In this paper, we build such a face image set from Yale face database B and the extended Yale face database B which consists of face images of different persons with the same pose and under the same frontal uniform illumination condition (refer to Section 4.1 Experiment Environments and Fig. 3 and 6).

Let us denote the PCA model deriving from such a face image set as follows.

\[
t = \mu + \Phi_{\text{identity}}^* b_{\text{identity}}^*
\]

But, one may note that illumination effects are not completely eliminated from \( \Phi_{\text{identity}}^* \) in (5).

3.2.2 Construction of an intrinsic illumination PCA model

In order to construct an face Gabor illumination PCA model, we build a face image set which consists of several face images of the same person with the same pose as in the face image set employed in 1) but under various illumination conditions. In this paper, we build such a face image set from Yale face database B with 64 different illumination conditions (refer to Section 4.1 Experiment Environments and Fig. 5).

Since face images in the face image set are of the same person of the same pose but with different illumination conditions, PCA analysis produces PCA modes which reflect variations of illumination. Also, since all face images of the image set comes from the same person with the same pose but under different illumination conditions, the obtained major PCA modes reflect illumination variations only. Since human faces are similar, the illumination variations are similar for every faces. Thus one can assume the matrix consisting of the major PCA modes as the face Gabor illumination PCA model \( \Phi_{\text{illum}} \).

3.2.3 Construction of Face Gabor Intrinsic Identity PCA model

As stated in Section 3.2.1, \( \Phi_{\text{identity}}^* \) contains the effects of the illumination and is not guaranteed to be orthogonal to the face Gabor illumination PCA model \( \Phi_{\text{illum}} \) in Section 3.2.2. In order to resolve these problems, one needs to orthogonalize \( \Phi_{\text{identity}}^* \) with respect to \( \Phi_{\text{illum}} \) to obtain a face Gabor intrinsic identity model \( \Phi_{\text{identity}} \).

The orthogonalization can be achieved by projecting \( \Phi_{\text{identity}}^* \) into the orthogonal subspace of \( \Phi_{\text{illum}} \) as follows.

\[
\Phi_{\text{identity}} = [I - \Phi_{\text{illum}}^T \Phi_{\text{illum}}] \Phi_{\text{identity}}^*
\]

Then, we now finally construct a Face Gabor space intrinsic PCA model as follows.

\[
t = \mu + \Phi_{\text{identity}} b_{\text{identity}} + \Phi_{\text{illum}} b_{\text{illum}}
\]

3.3 The proposed Face Recognition based on Face Gabor Intrinsic Identity PCA Model

For registration, we utilize one face image per pose for each registering person. The registration process is done as follows. First, face Gabor feature vector from each normalized face image is extracted and projected into the face Gabor intrinsic identity subspace spanned by \( \Phi_{\text{identity}} \). And then, the obtained projection coefficients \( b_{\text{identity}} \) are stored in the person identity database.

For face recognition phase, the face Gabor feature vector from the incoming normalized face image is extracted and projected into the face Gabor intrinsic identity subspace \( \Phi_{\text{identity}} \). The similarity between the obtained projection coefficients and each stored coefficients are compared and the person of the registered face image with the highest similarity is determined to be the person of the incoming face image.

4 EXPERIMENTS

4.1 Experiment Environments

In order to verify the effectiveness of the proposed method, we use the combination of Yale face database B and the extended Yale face database B which are popularly adopted for testing the performance of face recognition algorithms with respect to variations of
illumination.

Yale Face database B [12] consists of 5,850 images of 10 people (Fig. 3) under 9 different poses (Fig. 4) and 65 different illumination conditions (Fig. 5). Each image is grey image of pgm format with 640x486 pixels. Fig. 3 shows some sample images of Yale face database B. Fig. 4 shows 9 pose face images of the same person.

Fig. 5 shows some sample face images of the same person under different illumination conditions.

All face images used in the experiments have been geometric normalized into a size of 256x256 with the same fixed eye coordinates using the given eye coordinates. Eye coordinates of each face images are provided in Yale face database B and the extended Yale face database B. Fig. 7 shows a result of geometric normalization for a sample face image.

In order to evaluate the effectiveness of the proposed face recognition based on face Gabor intrinsic identity PCA model, we register 38 face images with frontal illumination of 38 persons per each pose and test the face identification for the remaining face images in the face database for each pose. That is, testing images consist of 38 (persons) x 9 (poses) x 63 (illumination conditions). The adopted decision rule for face identification is to determine the person of the testing face image as the person of the registered face image which has the highest similarity with the testing face image.

4.2 Experiment Results

We compared three face recognition methods: the conventional PCA based face recognition method without any illumination preprocessing (PCA), the PCA based face recognition method with anisotropic smoothing illumination normalization (ANI-PCA), and the proposed face recognition method based on face Gabor intrinsic identity PCA model (PROPOSED).

The extended Yale face database B [13] contains 16380 images of 28 human subjects under 9 poses and 65 illumination conditions. The data format of this database is the same as the Yale Face Database B. Fig. 6 shows some sample images of the extended Yale face database B.

Thus, in total our face database used in this paper consists of 21888 face images of 38 people under 9 different poses and 64 different illumination conditions.
mode subspace of each pose and compares the obtained projection coefficients with the stored projection coefficients of the registered images of that pose and determines the person of the incoming face image as the person of the registered image with the highest similarity.

The PCA based face recognition method with anisotropic smoothing-based illumination normalization is parallel to the conventional PCA based face recognition method except the fact that anisotropic smoothing-based illumination normalization is applied before registration and testing processing phase start.

The proposed face recognition method is processed per pose as explained in Section 3.3. Table 1 summary the experimental results.

TABLE 1 COMPARISON OF FACE IDENTIFICATION METHODS

<table>
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<th>POSES</th>
<th>METHODS</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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</thead>
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<td></td>
<td>PCA</td>
<td>90.49</td>
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<td>93.08</td>
<td>94.37</td>
<td>92.02</td>
<td>92.67</td>
<td>95.34</td>
<td>94.90</td>
<td>95.99</td>
</tr>
<tr>
<td></td>
<td>ANI-PCA</td>
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<td>96.88</td>
<td>97.65</td>
<td>98.02</td>
<td>97.37</td>
<td>94.82</td>
<td>96.56</td>
<td>98.87</td>
<td>98.46</td>
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<tr>
<td></td>
<td>PROPOSED</td>
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<td>97.41</td>
<td>98.06</td>
<td>98.50</td>
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<td>98.36</td>
<td>97.94</td>
<td>99.03</td>
<td>98.66</td>
</tr>
</tbody>
</table>

The experimental results of Table 1 shows that the proposed face recognition method based on face Gabor intrinsic identity PCA model is more robust to illumination variations compared to other methods.

5 CONCLUSIONS
In this paper, we analyzed face Gabor feature space, constructed a face Gabor intrinsic identity PCA model and proposed an illumination-robust face recognition method based on the face Gabor intrinsic identity PCA model. Since the face Gabor intrinsic identity subspace is independent of illumination effects, the projection of face Gabor feature vector extracted from an incoming face image is relatively unaffected by the illumination variations, so that the face recognition based on the face Gabor intrinsic identity model is robust to illumination variations. The effectiveness of the proposed method is verified through experiments.

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