Extracting Illumination Invariant Face Representation

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Abstract

Effective computer face recognition requires successful extraction and representation of the relevant information. In this paper the face structure signal and the illumination signal are analyzed in frequency domain. Non-linear methods are then proposed to achieve a illumination invariant face representation. Face images in two different databases are analyzed and recognized with this new representation. The experiments show that even for images taken under substantially changed lighting conditions, the representation is invariant to changes in both direction and intensity of illumination. As a result, the performance of the recognition system utilizing principal component analysis is improved significantly in two aspects: higher correct recognition rate and fewer principal components.

Keywords: non-linear filtering, face recognition, principal component analysis

1 Introduction

Face perception and recognition plays an important role in social communication. It seems that ordinary people are very sensitive to variations of the face shape and color but insensitive to changes of illumination conditions, pose, scale etc. But automatic extraction and representation of the relevant information for face recognition is still a challenging problem in computer vision. Recently, Turk and Pentland represent faces using Karhunen-Lóeve expansion or principal component analysis, also known as eigenface method. This defines a face model by using the principal components, which are projections of face images into a subspace stretched by eigenvectors of the covariance or correlation matrix of a set of face images [2]. Although by utilizing the eigenface method principal axles can be automatically determined via maximizing the covariance or correlation of *face images* in a training set [3], [4], distinction can not be made between the variance of images caused by relevant and irrelevant factors. Therefore, for face recognition utilizing eigenface method, it is important to develop a face representation invariant to changes of acquisition conditions and use that instead of grey-level face image as the input of Karhunen-Lóeve expansion.

The compensation of the variation caused by change of illumination conditions is one of the direct ways to develop an illumination invariant face representation. In [9] several image representations that are often considered insensitive to changes of illumination conditions, such as edge maps, derivatives of the grey-level image, and the image convolved with Gabor filter, are studied in details. They are mainly linear transformations corresponding to low-, high- or band-pass filters in the spatial-frequency domain [9]. The results of this study show that such kind of representations are insufficient to compensate the image variations caused by changes of illumination conditions. The best result is obtained by representations that emphasize the horizontal features. But even for these representations, up to 30% faces in the database are mis-recognized [9].

In this paper non-linear image precessing methods are proposed based on analysis of the face images in the frequency domain. The paper is organized as follows. Section 2 describes the non-linear methods for producing the illumination invariant face representation. Section 3 analyzes the results obtained from experiments using the new face representation. Section 4 gives a short conclusion.

2 Illumination Invariant Face Representation

The changes of illumination conditions involve changes in both direction and intensity. In this section, we first analyze the illumination signal and the reflection signal in frequency domain with help of a well-known model of the image acquisition process. Based on this model, the principle of compensating changes in lighting directions is given. The model is no longer exactly appropriate if, e.g. the angle of incidence light departs from 90° remarkably, or the image contrasts are poor. We discuss these difficulties and the possibilities to overcome them.

Techniques to standardize the illumination intensity is also presented.

2.1 Eliminating Changes of Illumination Direction

At first, the effect of changes of illumination conditions is considered in spatial-frequency domain with the following model:

$$f(x,y) = R(x,y) \cdot I(x,y) \tag{1}$$

where $f(x,y)$ is the image grey-level function, $R(x,y)$ the reflection part and $I(x,y)$ the illumination part. This model provides a good approximation of the image-acquisition process for many practical cases [11], [12]. The relevant face information is normally only contained in the reflection part $R(x,y)$. But as shown in Fig.1, normal low-, high-, band-pass filters are insufficient to separate the $R(x,y)$ from $I(x,y)$.

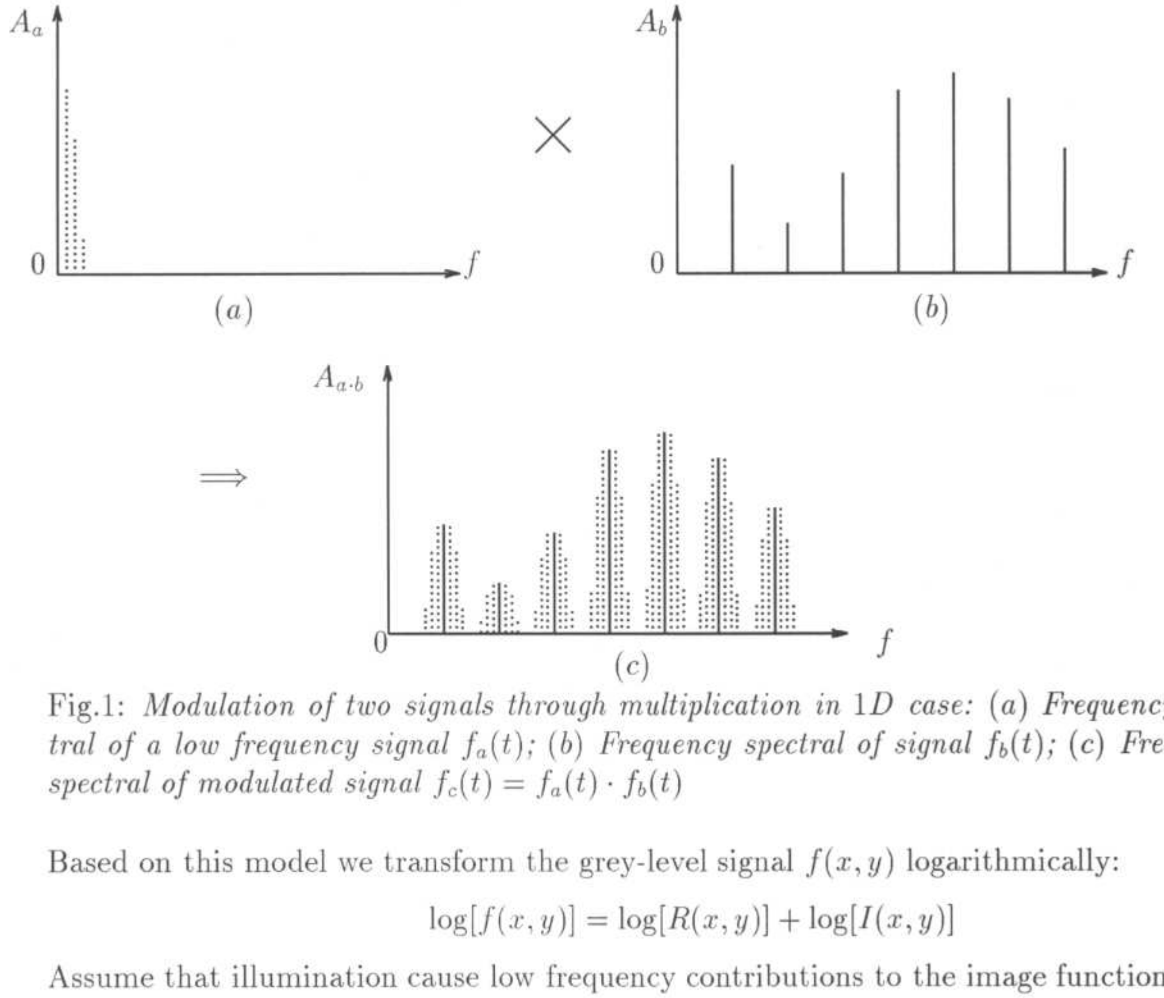


Fig.1: *Modulation of two signals through multiplication in* $1D$ *case:* (a) *Frequency spectral of a low frequency signal* $f_a(t)$*;* (b) *Frequency spectral of signal* $f_b(t)$*;* (c) *Frequency spectral of modulated signal* $f_c(t) = f_a(t) \cdot f_b(t)$

Based on this model we transform the grey-level signal $f(x,y)$ logarithmically:

$$\log[f(x,y)] = \log[R(x,y)] + \log[I(x,y)] \tag{2}$$

Assume that illumination cause low frequency contributions to the image function and the individual $3D$ shape in a higher frequency range. The illumination signal can then be separated from the reflection signal and filtered out with a normal high-pass filter, as shown in Fig.2. The cut-off frequency radius (CFR) of the high-pass filter is normalized to the longest image dimension. The face signal which eliminates the illumination influence is received by transforming the filtered signal exponentially.

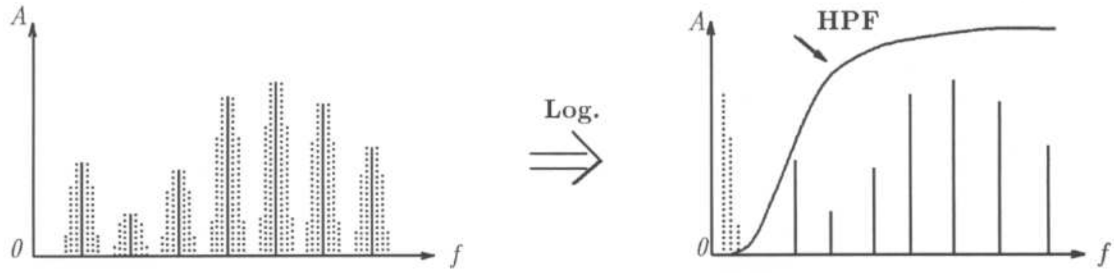


Fig.2: *The frequency spectral of two modulated signals before and after the logarithmic transformation in 1D case. Ideally they are completely separable with a normal linear filter.*

Two problems arise if the angle of light incidence differs from 90° considerably.
1. As the high-frequency component in the illumination parts increases, or as the contrast of the image decreases, the frequency spectra of both parts become inseparable.
2. The face structure in the image is changed due to shadows on the face (Fig.3).

(a) (b) (c) (d)

Fig. 3: *Faces with shadows.*

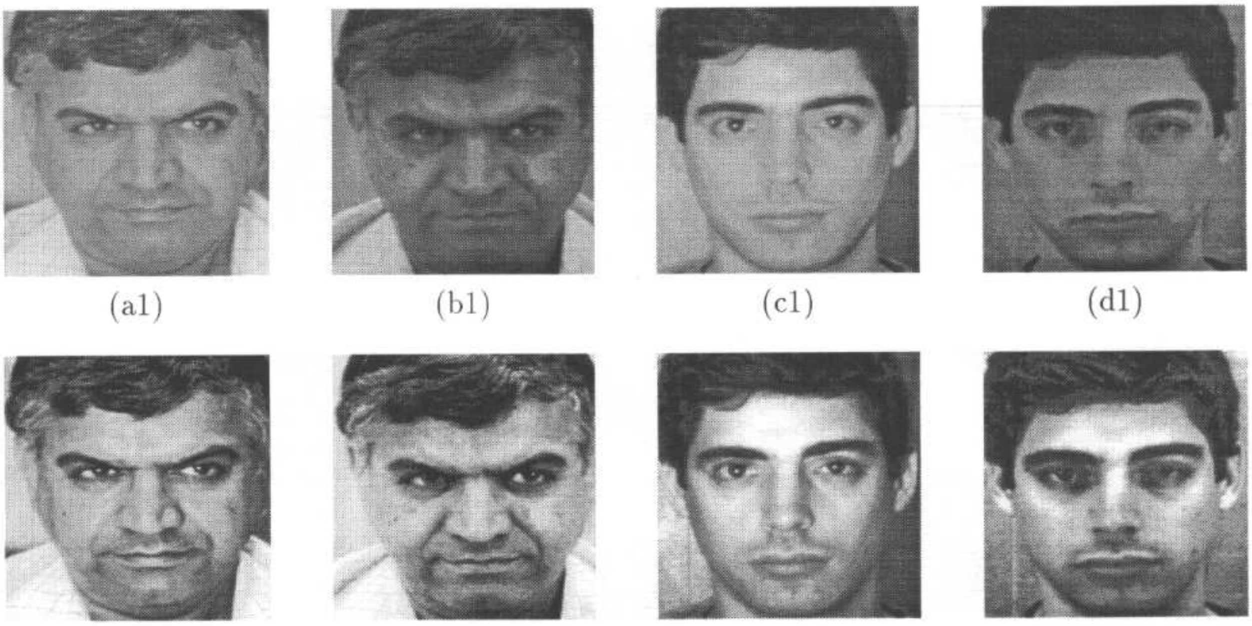
To solve the problem 1, different techniques can be used before the non-linear transformation to lift up the high frequency components of the image so that the reflection and illumination part can be separated, at least partly, again, for instance, the unsharp-marking.

Since no geometric face-model is used, it is very difficult to remove shadows completely. But shadows appear normally only on chin if the incident angle is not near to 0° or 180°. Fortunately, less information for face recognition is contained in chin than in other regions [1]. They can be thus removed by sacrificing parts of low-frequency components.

2.2 Eliminating Changes of Illumination Intensity

Even small changes of illumination intensity may cause irrelevant variations of face images. It is therefore necessary to normalize the intensity before the principal component analysis, specially for small databases.

Different ways have been tried to compensate changes of illumination intensity. E.g. normalizing the mean of grey-level, histogram equalization etc. The histogram equalization transforms the grey-level density function into a constant one [11]. The effect of the histogram equalization on face images taken under different illumination intensities is demonstrated in Fig. 4.



(a1) (b1) (c1) (d1)

(a2) (b2) (c2) (d2)

Fig.4: *Images taken under different illumination intensity. Upper row: original images; low row: images processed with the histogram equalization*

It shows that after the histogram equalization the difference of image intensities are much smaller then that of the original images.

The whole process of the proposed method to compensate changes of direction and intensity of illumination is composed of three steps (Fig.5):

The first step is to improve the image contrast and emphasize the high frequency components. The second step is to separate the illumination signal and reflection signal using homomorphic filter. The last step is to standardize the lighting intensities.

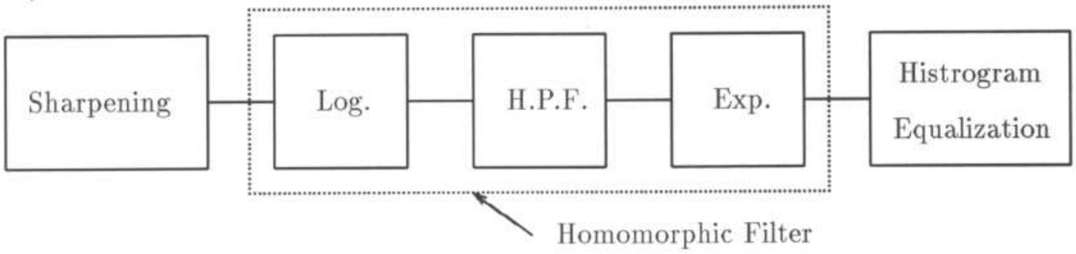


Fig. 5: *Process of compensating changes of illumination conditions*

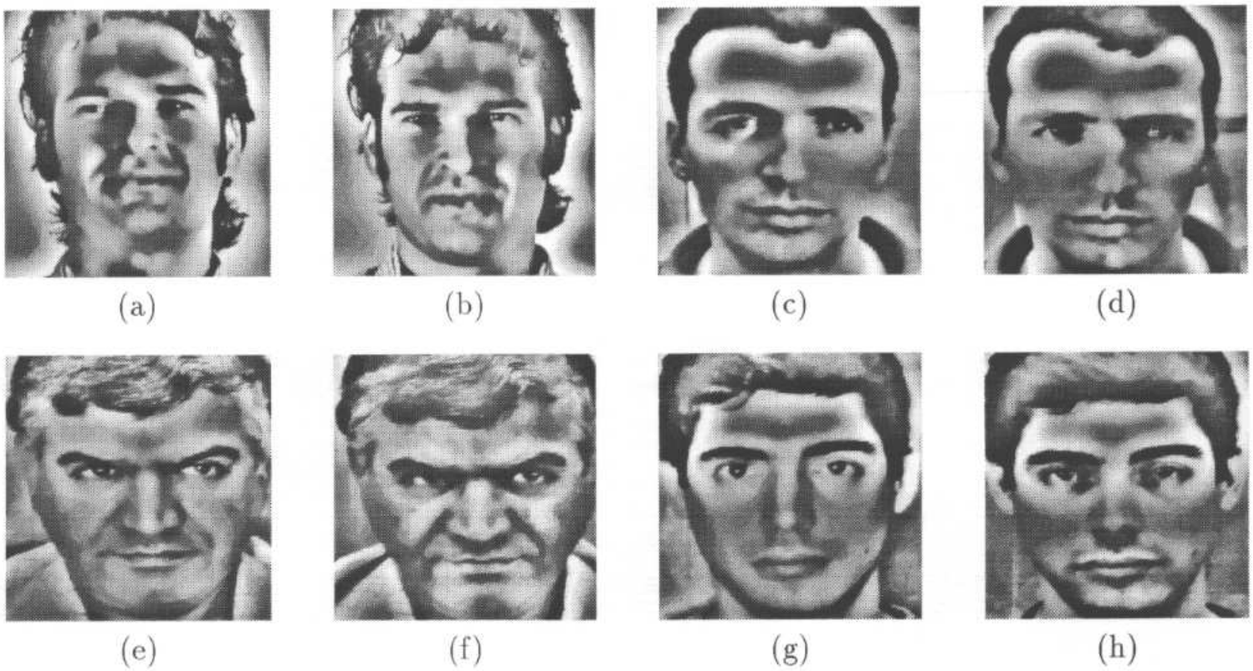


Fig. 6: *Illumination invariant face images*

In Fig.6 are face images resulted from the proposed method to compensate the changes of illumination conditions. The original images are contained in Fig.3 and Fig. 4 respectively. It can be seen that both the lighting direction and lighting intensity are standardized. Shadows are removed successfully. Although parts of the low frequency components are lost, the important face features are well preserved.

3 Experiments and Results

The proposed method is applied to two different face databases (fdbs). The illumination conditions in these two fdbs are controlled in different ways. The fdb1 consists of 65 face images from 35 persons. Subjects are Europeans and Asians between 20 and 40 years old, 15 female and 20 male. Nobody wears glasses and has beard. Only frontal images are used. Images are taken under very soft light, reflected from two polystyrene surfaces standing on both left and right side. This is to simulate the natural light. The lighting direction and intensity are changed only slightly. The fdb2 is one part of the fdb used in [9]. The acquisition parameters in that database like illumination condition, view and expression are controlled strictly separately. Since changes of illumination conditions are the main concern of this work, 104 frontal face images from 26 male subjects with normal expression are chosen. Subjects have also no glasses and beard. The lighting conditions change in direction and intensity.

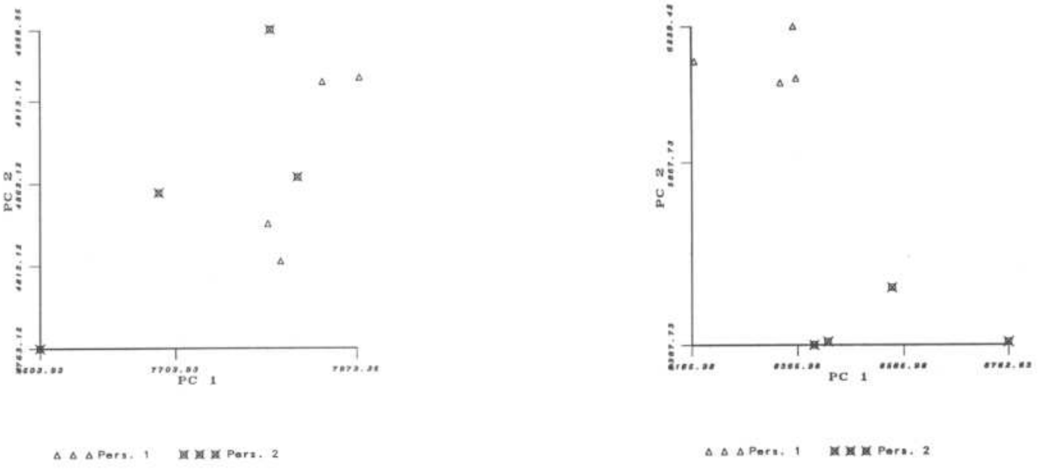
In the first experiment, Euclidean distances (Eds) among face images are measured before and after the compensation in order to present its effect on the distributions of face images. In the second experiment, the original grey-level face images and the new face representations are transformed with KLT. The results of face recognition are given to show the improvement of the system performance.

3.1 Image Distribution

In fdb1 large variation in individuals occurs due to changes in gender, nationality and expression of the subjects, whereas the variation caused by changes in lighting conditions is small. In contrast, small variation of individuals appears under strong changed lighting conditions in fdb2. In this experiment the distribution of face images, in both original face space and eigenface space, are compared before and after the illumination compensation.

In the original face space, the Euclidean distances (Eds) among face images are measured. Before the compensation, even as illumination conditions are changed slightly, just like in fdb1, the Eds between images from the same subject (SSd) are not always smaller than images from different subjects (DSd). There are 12 SSds of total 48 SSds larger than few or more DSds. When the change of the illumination conditions becomes more substantial, as in fdb2, the distances among the original images are mainly decided by lighting conditions, i.e. DSds are nearly always larger than SSds, just like described in [9]. After the processing of images with the non-linear methods, no more SSd in fdb1 is larger than any DSds. Even in the fdb2, the distribution of face images is significantly improved, i.e. images from same subjects are moved to lie more closely than images from different subjects. Only 3 SSds out of 156 SSds are still larger than a few DSds.

For the graphic representation some of the original face images and their invariant face representation in the fdb2 are projected into the low eigenface space, stretched by the first two eigenvectors of the covariance matrix (Fig.7). It is clear that before the compensation, images of different subjects are mixed together (Fig 7(a)), After the compensation however, these images are well separated (Fig.7(b)).



(a) (b)

Fig.7: *Distribution of face images in eigenface space stretched by the first two eigenvectors. (a) Distribution before the illumination compensation (b) Distribution after the illumination compensation.*

3.2 Face Recognition

In the second experiment, face images in the fdb2 are identified before and after the compensation. Two aspects of the identification are obtained in the experiment, namely the rate of correct identification and the numbers of PCs used. The method of identification is the same as presented in [2]. For every subject, a mean vector is calculated. Then the Eds between the PC-vector of the face to be identified and every mean vector are measured. The face is identified as that person to whom it has the minimal Ed.

Fig.8: *The first* 10 *eigenfaces of fdb2 before the illumination compensation*

As shown in Fig.8, the eigenfaces corresponding to the largest eigenvalues are turned to point to the directions of illumination changes. This particularly appears in the first four eigenfaces. The relevant PCs contain hence more variation of illumination than that of face structure. Thus 100% of faces in the fdb2 are mis-identified even with all the 104 PCs.

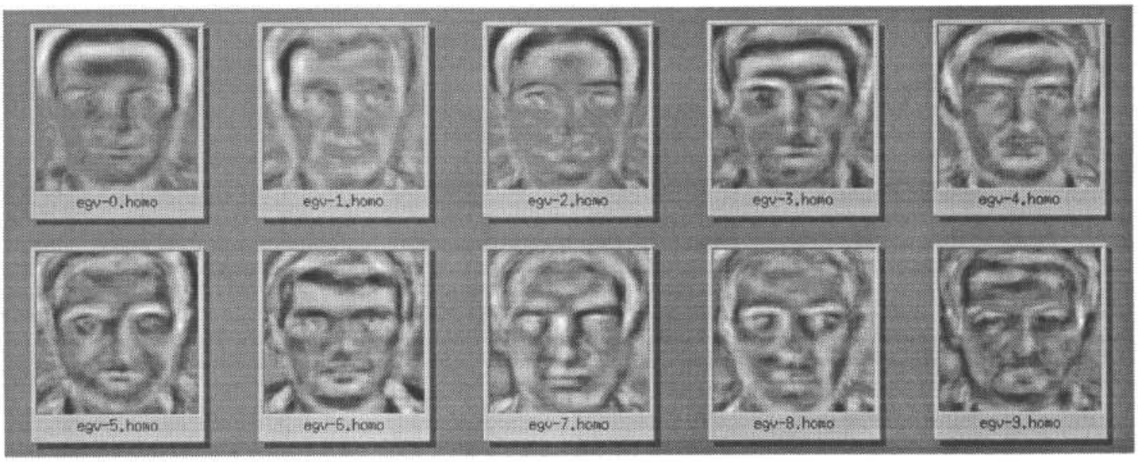


Fig. 9: *First* 10 *eigenvectors of fdb2 after the illumination compensation*

After the compensation the first 10 eigenfaces are shown in Fig.9. The eigenvectors corresponding to the largest eigenvalues contain less information of lighting condition variation comparing with the eigenvectors shown in Fig.8. If all of 104 PCs are applied to identification, the correct rate is 100%. As the numbers of PCs decreased to 70, still 91% of all the faces are correctly identified.

4 Conclusion

To analyze face images with statistical methods, it is very important to extract the relevant information and ignore the irrelevant information. Linear filters are insufficient to separate the face signal and the illumination signal. But the illumination invariant face representation can be achieved by applying non-linear methods, such as homomorphic filter, histogram equalization, etc. From the two experiments presented in section 3, it can be concluded that this new representation is invariant against changes in both direction and intensity of the illumination. The distributions of face images are greatly ameliorated. The eigenfaces corresponding to the largest eigenvalues contain more relevant information of the face structure. The system utilizing principal component analysis can thus recognize faces with higher correct rate by using fewer principal components.

Acknowledgments

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