Face Recognition using Principal Component Analysis of Gabor Filter Responses

Ki-Chung Chung, Seok Cheol Kee and Sang Ryong Kim
HCI Lab., Samsung Advanced Institute of Technology
San 14, Nongseo-Ri, Kiheung-Eup, Yongin City, Kyungki-Do, 449-712, Korea
{kcchung, sckee, srkim}@sait.samsung.co.kr

Abstract

This paper addresses new face recognition method based on Principal Component Analysis(PCA) and Gabor filter responses. Our method consists of two parts. One is Gabor filtering on predefined fiducial points that could represent robust facial features from the original face image. The other is transforming the facial features into eigenspace by PCA, which is able to classify individual facial representations optimal. Thus, trained face model has some eigenvalues that can be derived from ensemble matrix of given Gabor responses. In order to identify the faces, test images are also projected into eigenspace from image space and compared to the trained face images in the same eigenspace. The basic idea of combining PCA and Gabor filter is to overcome the shortcomings of PCA. When raw images were used as a matrix of PCA, the eigenspace cannot reflect the correlation of facial feature well, because original face images have deformation due to in-plane, in-depth rotation and brightness and contrast variation. So, we have overcome these problems using Gabor filter responses as input. Gabor filter has the robust characteristics in illumination and rotation. In addition, we confirmed the improvement of discrimination ability when Gabor responses had transferred to the space constructed by the principal components. The experimental results show that the proposed method achieves the remarkable improvement of recognition rate of 19% and 11% compared to conventional PCA method in SAIT dataset and Olivetti dataset respectively. And, our method has excessive advantage in gallery DB size than recognition method only using Gabor filter responses.

1. Introduction

Face recognition is one of the important research topics and many researchers are trying to achieve successful results, since it has the possibility of many applications, such as security system and human-computer interface and so on[1]. There have been a lot of methods proposed for face recognition. These are divided into two categories: local feature matching method and holistic matching method. The representative method of holistic matching is PCA[4]. The basic idea is to construct a new space that can represent input data with lower dimensional feature vectors. But, PCA has much restriction in applying to face recognition, because the input face images must be ideally aligned and under well-controlled illumination. In addtion, holistic matching can not describe local variation of face, so a method that can compensate for this shortcoming is required. It is well known that Gabor filter responses are effective in description of local feature[5]. In this paper, we propose new face recognition method that can overcome the problems of PCA using Gabor filter responses.

2. Principal Components Analysis of Gabor Filter Responses

2.1. Principal Component Analysis

Principal Component Analysis(PCA) is a standard technique used to approximate the original data with lower dimensional feature vectors[2]. The $N \times N$ face image can be expressed as a point in the $N \times N$ dimensional space. Then the ensemble of face images can be expressed as congregation of points in image space. The purpose of PCA is to find the appropriate vectors that can describe the distribution of face images in image space and form another space. Let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3, \cdots, \Gamma_M$. The average face of the set is defined by $\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$. Each face differs from the average by the vectors $\Phi = \Gamma_i - \Psi$. The eigenvalues and eigenvectors are obtained from covariance matrix (1) and a new face image is transformed into its face components by this operation[4],

$$C = \frac{1}{M}\left[\sum_{n=1}^{M}\Phi_n\Phi_n^T\right] \tag{1}$$

The weights form a vector $\Omega = [\omega_1, \omega_2, \ldots \omega_M]$ that describes the contribution of each eigenvector in representing the input face image, treating the eigenvector as a basis set for face images.

$$\omega_k = u_k^T(\Gamma - \Psi), k = 1, 2, \ldots, M \tag{2}$$

where u_k is eigenvector. These weights may be used in a face classification algorithm to find which of predefined face classes that describe the face.

2.2. Gabor Filter Responses

The processing of facial images by Gabor filter is chosen for its biological relevance and technical properties. The Gabor filter kernels are similar shapes as the receptive fields of simple cells in the primary visual cortex. In other words, they are multi-scale and multi-orientation kernels. The response describes a small patch of gray values in an image $I(x)$ around a give pixel $x = (x, y)$. It is defined as a convolution

$$J_i(\overrightarrow{x}) = \int I(\overrightarrow{x}')\Psi_j(\overrightarrow{x} - \overrightarrow{x}')d^2\overrightarrow{x}' \tag{3}$$

$$\begin{aligned} \Psi_j(\overrightarrow{x}) &= \frac{k_j^2}{\sigma^2}\exp(-\frac{k_j^2 x^2}{2\sigma^2}) \\ &\quad \exp[\exp(i\overrightarrow{k}_j\overrightarrow{x}) - \exp(-\frac{\sigma^2}{2})] \end{aligned} \tag{4}$$

with a family of Gabor filters in the shape of plane waves with wave vectors k_j, restricted by a Gaussian envelope function. We employ a discrete set of 5 different frequencies, index $\nu = 0, \ldots, 4$ and and 8 orientations, index $\mu = 0, \ldots, 7$ with index $j = \mu + 8\nu$. Gabor filter sets provide robustness against varying brightness and contrast in the image.

$$\overrightarrow{k}_j = (\frac{k_{jx}}{k_{jy}}) = (\frac{k_\nu \cos\varphi_\mu}{k_\nu \cos\varphi_\mu}), \tag{5}$$

where

$$\begin{aligned} k_\nu &= 2^{-\frac{\nu+2}{2}}\pi, \\ \varphi_\mu &= \mu\frac{\pi}{8}. \end{aligned}$$

2.3. Principal Component Analysis of Gabor Filter Responses

Principal Component Analysis (PCA) uses face image as input data, then it should be aligned well and should not include some in-plane and in-depth rotation. The face region should be extracted from the original image and the brightness and contrast should be stable, too. Due to these problems, it's difficult to use PCA in real environment. So we are trying to overcome these shortcomings of PCA by keeping the basic concept that the most distinctive features act as a basic axis in the space. The responses of Gabor filter have some useful characteristics. First, it provides robustness against varying brightness and contrast in the image. Second, it can represent the characteristics of the local face area, so it's more effective than using the original face image directly. We propose a method that uses Gabor filter response as an input of PCA instead of raw face image to overcome the shortcomings mentioned above. Using the Gabor filter responses as input vector, the sensitive reaction due to the rotation and illumination can be reduced. And if we transfer the Gabor filter responses into another space that is based on the principal axis, the face images will be arranged more effectively for classification. To use the Gabor filter response, we should get the magnitude value from the real and imaginary part value. Because the real and imaginary parts are too sensitive in spite of the slight displacement, it cannot be used directly. For example, let the number of fiducial points that can get the Gabor filter responses are N, we can select the 40 magnitude values using (3) and (4) from N points and construct the $N \times 40$ dimensional array. And if we use M gallery images, construct ($N \times 40$) by M matrix could be constructed and the eigenvalues and eigenvectors can be calculated form the ensemble matrix AA^T, where the matrix $A = N \times 40$ by M matrix. From the eigenvalues, we can select the effective Gabor filter responses and construct the eigen space with the appropriate number of eigenvectors. Then the training sets of face image are projected in the eigen space and the testing set of face images are also projected according to the equation (2). The weight values of the projection into the eigen space are the characteristics of the new face image. To compare the similarity of the values in the eigen space, we used similarity function [3].

$$S_a(J, J') = \frac{\sum_j a_j a_j\prime}{\sqrt{\sum_j {a_j}^2 \sum_j {a_j\prime}^2}} \tag{6}$$

In PCA, euclidean distance measure was used to estimate the similarity [4], but we confirmed that similarity function is more effective in eigen space.

3. Experiment

To process the face images, we manually locate the eyes and then perform geometric normalization with the eye locations fixed and perform intensity normalization, size normalization. And we used 12 fiducial points that were selected from the relative distance of two eye points. The normalized face image size is chosen to be 128×128. We used two kinds of face dataset : One is SAIT face dataset which is organized by ourselves and composed of 320 images from 40 galleries constructed under various illumination condition. Another is Olivetti face dataset that is composed of 400 images from 40 galleries which is constructed under various depth and plane rotation. Some examples of face dataset are shown in Figure 1 and Figure 2. SAIT face dataset is composed of 8 face images per a person, so we have constructed 8 sets. To process the experiments, we defined one as training set and the other 7 sets as testing sets in turn. Olivetti face dataset is composed of 10 face images per a person, so we have constructed 10 sets. And as the SAIT face dataset, we defined one as training set and the other 9 sets as testing sets in turn. We've selected 12 fiducial points about one face image, and made 480 dimensional array using 40 magnitude values about each point. Then we constructed 40 by 480 matrix, where the row vector was the data of a testing face image. And we obtained eigenvalues and eigenvectors from its 40×40 ensemble matrix. To construct the eigen space, we selected 40 valid eigenvalues and obtained the weight vectors by projecting the training and testing set of face images. To recognize the individuals, we compared the weight vectors using similarity function [5].

Figure 1. Face images of SAIT face dataset

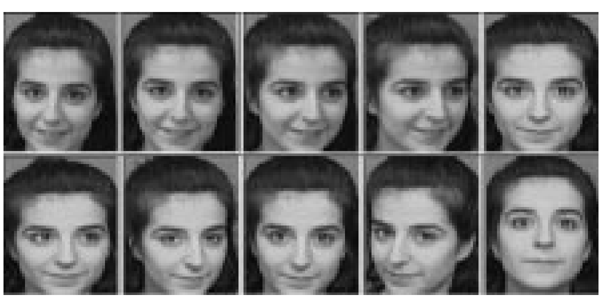


Figure 2. Face images of Olivetti face dataset

3.1. Comparison of PCA and PCA of Gabor Filter Responses

The experiment results are shown in Figure 3. We can confirm the remarkable improvement of recognition rate of 19% in figure 3(a). It shows that PCA is weak against various illuminations. And figure 3(b) shows the improvement of 11%. Also it shows that pose variation is another drawback of PCA. And we confirm that the recognition rates are similar in spite of the variation of the resolution of face images. It shows that the radical variation of pixel brightness can be an obstacle in PCA.

3.2. Comparison of Gabor Filter Response and PCA of Gabor Filter Response

Figure 4 shows the recognition rate of Gabor filter response and suggested method. We can confirm the improvement of recognition rate of 4.5% and 5% in SAIT dataset and Olivetti dataset respectively. Although the progress of recognition is rather slight, it is a great experimental result considering the reduction of gallery DB size. We can reduce the size of gallery DB to 1/12 times smaller than that of original Gabor filter method.

4. Conclusion

In this paper, we have presented the face recognition system that combines Gabor filter method and PCA. Because face images are very sensitive to illumination and pose variation, we anticipated that the drawback could be overcome by using Gabor filter responses as an input of PCA. The experiment result was reasonably acceptable i.e. the space transfer of Gabor filter responses based on principal component vectors was successful in classification and discrimination. We will study the construction of eigen space axis by selecting meaningful principal component and by deleting the axis working as a noise component. In the future, it is desirable to research on another representation method, rather than Gabor filter, that can describe face image robustly against illumination and pose variation. The classification and discrimination method is another research topic in future work.

Acknowledgments:

References

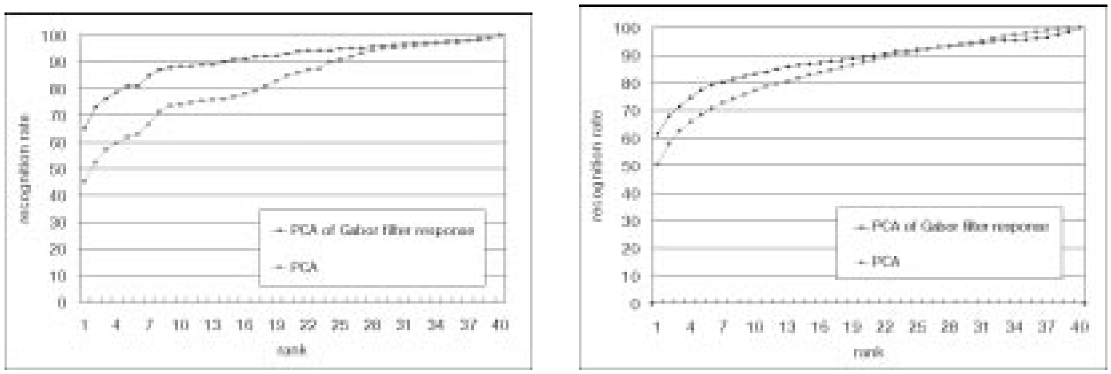
[1] R. Chellappa, C. L. Wilson, and S. Sirohey. Human and machine recognition of faces, a survey. *Proc. of the IEEE*, 83:705–750, 1995.

[2] K. Fukunaga. *Introduction to Statistical Pattern Recognition*. Academic Press, 1990.

[3] M. Lades, J. C. Vorbruggen, J. Buhmann, J. Lange, C. von der Malsburg, R. P. Wurtz, and W. Konen. Distortion invariant object recognition in the dynamic link architecture. *IEEE transactions on Computers*,, 42(3):300–311, 1993.

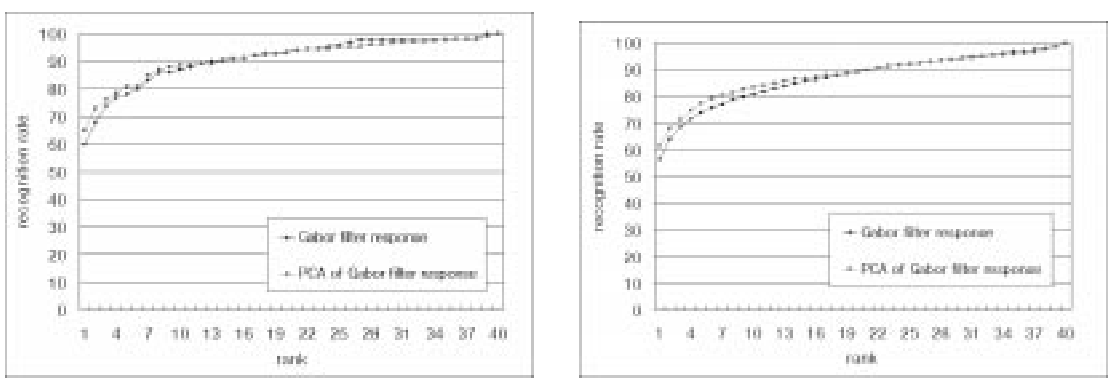
[4] M. Turk and A. Pentland. Eigenfaces for recognition. *Journal of Cognitive Neuroscience*, 3:72–86, 1991.

[5] L. Wiskott, J. M. Fellous, N. Kruger, and C. V. der Malsburg. Face recognition by elastic graph matching. *IEEE Trans. on Pattern Recognition and Machine Intelligence*, 19:775–779, 1997.



(a) (b)

Figure 3. Recognition result of PCA and PCA of Gabor filter responses (a)SAIT face dataset, (b)Olivetti face dataset



(a) (b)

Figure 4. Recognition result of Gabor filter response and PCA of Gabor filter responses (a)SAIT face dataset, (b)Olivetti face dataset